Agricultural Systems 198 (2022) 103388

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Review

Process-based greenhouse climate models: Genealogy, current status, and future directions

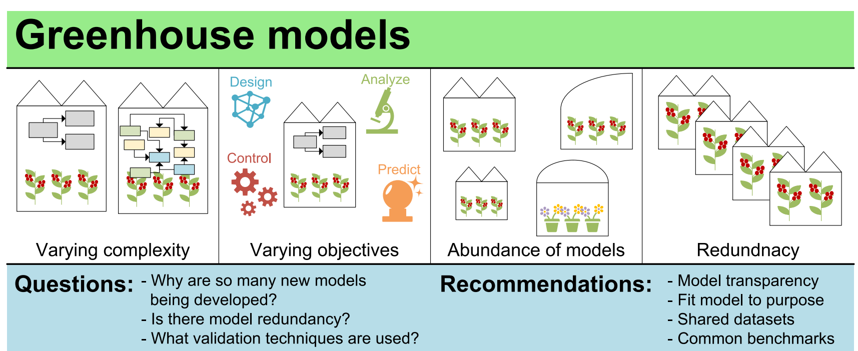
David Katzin [a,b,*], Eldert J. van Henten [a], Simon van Mourik [a]

[a] *Farm Technology Group, Department of Plant Sciences, Wageningen University, PO Box 16, 6700 AA Wageningen, the Netherlands*
[b] *Wageningen UR Greenhouse Horticulture, PO Box 644, 6700 AP Wageningen, the Netherlands*

HIGHLIGHTS

- Greenhouse models have been in use since at least the 1980's, and the number of new models is growing tremendously
- We analyze recently published greenhouse models in terms of their objectives, structure, inheritance, and evaluation
- We suggest that a main reason for the development of new greenhouse models is the lack of transparency of existing models
- Transparency, data sharing, benchmarks, and validation metrics are suggested as means to facilitate future development
- Developers are encouraged to reflect on and state their models' suitability, complexity, validity, and transparency

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Mark van Wijk

Keywords:
Review
Greenhouse model
Climate model
Crop model
Model evaluation
Model validation

ABSTRACT

CONTEXT: Process-based greenhouse climate models are valuable tools for the analysis and design of greenhouse systems. A growing number of greenhouse models are published in recent years, making it difficult to identify which components are shared across models, which are new developments, and what are the objectives, strengths and weaknesses of each model.
OBJECTIVE: We present an overview of the current state of greenhouse modelling by analyzing studies published between 2018 and 2020. This analysis helps identify the key processes considered in process-based greenhouse models, and the common approaches used to model them. Moreover, we outline how greenhouse models differ in terms of their objectives, complexity, accuracy, and transparency.
METHODS: We describe a general structure of process-based greenhouse climate models, including a range of common approaches for describing the various model components. We analyze recently published models with respect to this structure, as well as their intended purposes, greenhouse systems they represent, equipment included, and crops considered. We present a model inheritance chart, outlining the origins of contemporary models, and showing which were built on previous works. We compare model validation studies and show the various types of datasets and metrics used for validation.

* Corresponding author at: Wageningen UR Greenhouse Horticulture, PO Box 644, 6700 AP Wageningen, the Netherlands.
E-mail address: david.katzin1@gmail.com (D. Katzin).

https://doi.org/10.1016/j.agsy.2022.103388
Received 17 September 2021; Received in revised form 21 January 2022; Accepted 4 February 2022
Available online 24 February 2022

RESULTS AND CONCLUSIONS: The analysis highlights the range of objectives and approaches prevalent in greenhouse modelling, and shows that despite the large variation in model design and complexity, considerable overlap exists. Some possible reasons for the abundance of models include a lack of transparency and code availability; a belief that model development is in itself a valuable research goal; a preference for simple models in control-oriented studies; and a difference in the time scales considered. Approaches to model validation vary considerably, making it difficult to compare models or assess if they serve their intended purposes. We suggest that increased transparency and availability of source code will promote model reuse and extension, and that shared datasets and evaluation benchmarks will facilitate model evaluation and comparison.

SIGNIFICANCE: This study highlights several issues that should be considered in greenhouse model selection and development. Developers of new models can use the decomposition provided in order to present their models and facilitate extension and reuse. Developers are encouraged to reflect on and explicitly state their model's range of suitability, complexity, validity, and transparency. Lastly, we highlight several steps that could be taken by the greenhouse modelling community in order to advance the field as a whole.

1. Introduction

Mathematical modelling of greenhouse climate is the study dedicated to quantitatively describing horticultural greenhouses and the interrelationships between the outdoor weather, the indoor climate, the greenhouse structure, the climate control equipment, and the cultivated crop. This discipline sits at the intersection of several fields, including agricultural crop modelling, building engineering, and systems and control theory.

Greenhouse modelling dates back to at least 1958, with a model describing how water on the greenhouse roof influences the absorbed solar radiation (Morris et al., 1958). The first model describing the complete greenhouse system may be attributed to Businger (1963), who used mathematical equations to analyze the energy budget of a glasshouse. Since then, greenhouse modelling has been used as a research tool for synthesis and advancement of knowledge, as an educational device in the classroom, and as an aid to decision-making and policy analysis (Gary et al., 1998). In their role as decision aides, greenhouse models have been used for help with tactical management, operational control, and design of greenhouse systems (Lentz, 1998).

The greenhouse industry currently faces difficult challenges as it aims to increase production around the world while decreasing the use of resources such as energy and water (Marcelis et al., 2019). In their role as research tools, models can provide useful insights to help address these problems and to identify potential research directions in order to sustainably intensify production. At the same time, there is a growing interest by the greenhouse industry in the use of models and other data-based tools as an aid in management support and automation. Models are increasingly used in horticulture (Körner, 2019) as companies provide support tools based on modelling and prediction (B-Mex, 2020; Hoogendoorn Growth Management, 2020; Priva, 2019), and methods for greenhouse control based on artificial intelligence are being developed and tested (Hemming et al., 2019b).

The growing interest in greenhouse modelling results in a great number of published models. As early as 1985, Van Bavel et al. noticed "a proliferation of greenhouse climate models that may well confuse those that wish to solve practical problems by the simplest means possible" (Van Bavel et al., 1985). Around 1990, several reviews (De Halleux, 1989; Hölscher, 1992; Lacroix and Zanghi, 1990) collectively found 41 greenhouse models published over a period of nearly 30 years, from 1958 to 1986 (Von Zabeltitz, 1999). This list has since grown tremendously, with several recent reviews (Choab et al., 2019; Golzar et al., 2018; Iddio et al., 2020; Lopez-Cruz et al., 2018; Taki et al., 2018) collectively listing over 150 greenhouse models, more than 70 of them developed in the last decade.

It is unclear why so many greenhouse models are being developed. One possible explanation is that greenhouses are extremely versatile, differing in structure type, climate control equipment, cultivated crops, and purposes (Stanghellini et al., 2019). Accordingly, a vast range of goals and research questions may be posed regarding greenhouse operation. Another possible explanation is that models with similar purposes are being independently developed by different groups, creating model redundancy (Holzworth et al., 2015; Janssen et al., 2017).

Whatever the reason may be, the plethora of existing greenhouse models makes it difficult for newcomers to the field – researchers, developers, or other potential users of a model – to adequately choose the best model for their purposes. Soltani and Sinclair (2015) have listed several criteria that should be taken into account when selecting a model, including suitability, complexity, validity, and transparency. "Suitability" concerns the objectives that a model was designed to achieve; "complexity" concerns the number of parameters, processes or equations included in a model; "validity" (termed "robustness" by Soltani and Sinclair) describes the extent of the scenarios under which the model can generate accurate predictions; and "transparency" reflects the accessibility and clarity of the model structure and source code.

The purpose of this study was to provide an overview of the current status of greenhouse modelling. We focused on one category of greenhouse models, namely process-based models of the greenhouse climate, that consider the greenhouse air as a "perfectly stirred tank" (Roy et al., 2002), possibly divided into several compartments that are themselves perfectly stirred. We analyzed recently published models in this category in terms of their objectives, complexity, validity, and transparency. This categorization serves as an overview of greenhouse models, which provides a first step in the effort to explain why so many greenhouse models exist. We examined if and how models differ by determining their shared and distinct components and identifying which of those originate from previously published models, and which are new additions. In this way, two objectives are served: first, a framework for decomposing and analyzing greenhouse models is offered. An overview of recently developed models is laid out by this framework, allowing newcomers to make informed decisions about which model to use or build on. Second, a general overview of the current state of greenhouse climate modelling is provided. This overview is used to identify possible bottlenecks in the advancement of the field, suggest solutions on how these bottlenecks may be overcome, and outline further steps that can be taken to make improvements for the future of greenhouse modelling.

The rest of this paper is organized as follows: Section 2 provides some background on process-based greenhouse climate models, describing a general common structure that these models share and demonstrating with examples the possible range of complexity within this common structure. Section 3 details the methodology used in the review and

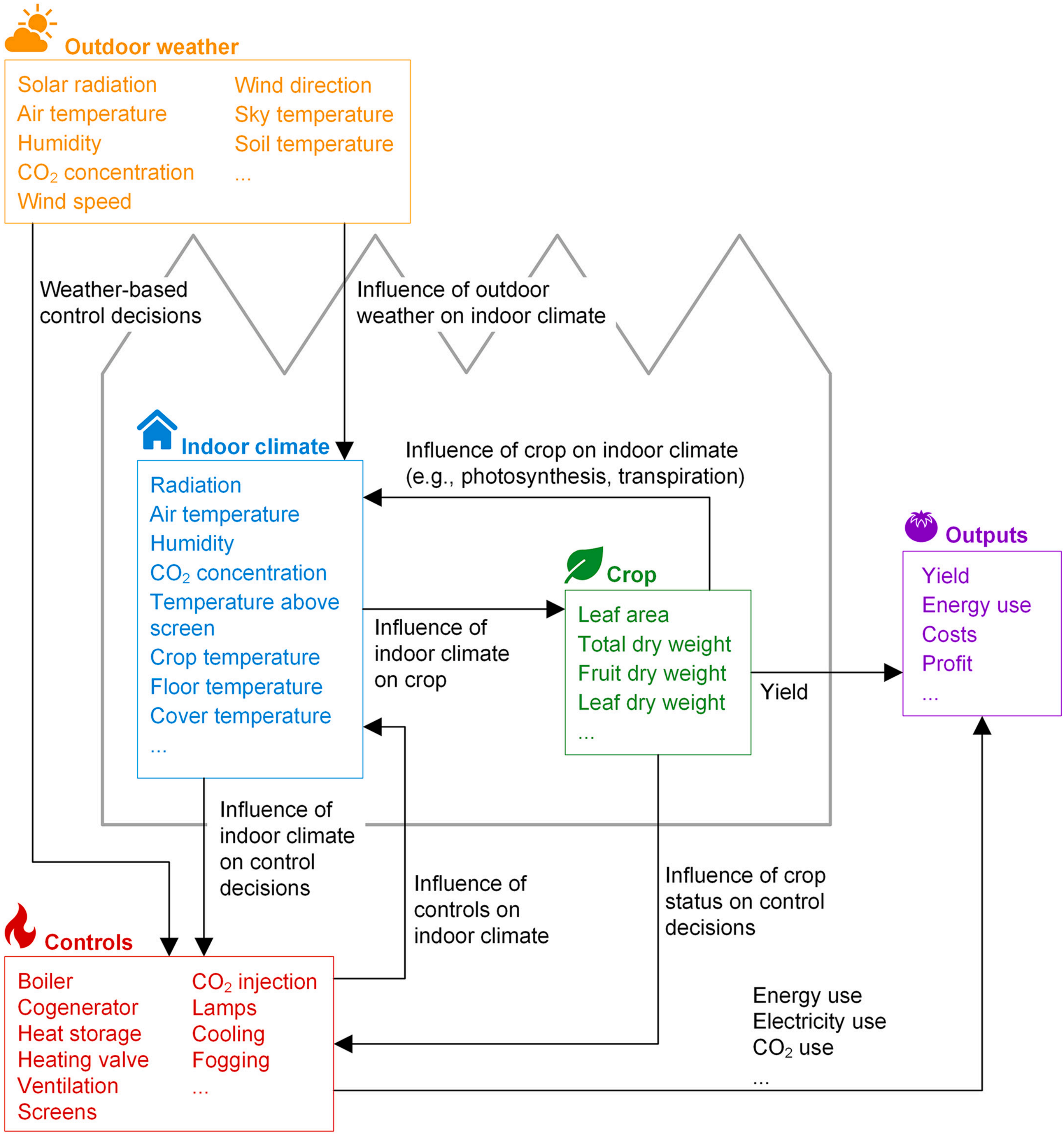


Fig. 1. Scheme of the greenhouse system. Control decisions are based on the outdoor weather, the indoor climate, and the crop status. The indoor climate is influenced by the outdoor weather, the controls, and the crop. The crop is influenced by the indoor climate. Some outputs are yield (which depends on the crop), costs and energy use (which depend on the controls). In this study we focus on the indoor climate and the processes influencing it.

analysis of process-based greenhouse climate models published between 2018 and 2020. Section 4 presents the results of this analysis, and Section 5 provides a discussion and reflection on the current state of greenhouse modelling in view of the results.

2. Background

2.1. Process-based greenhouse climate models and the "perfectly stirred tank"

As in other systems, greenhouse climate models may be broadly categorized as either descriptive (also termed empirical or black-box) or process-based (also termed mechanistic, explanatory, white-box, or grey-box) (Thornley and France, 2007). The distinction between the two categories, however, is not always clear, and they are better viewed as two edges on a spectrum (Keating and Thorburn, 2018). Descriptive models describe systems using equations based on mathematical or statistical grounds, regardless of underlying principles. In contrast, process-based models aim to provide an understanding or explanation of the system being investigated, typically by combining two levels of description, with a lower level describing observed scientific phenomena, and a higher level describing emergent properties based on these phenomena (Thornley and France, 2007). The expectation is that process-based models generalize better than descriptive models to conditions outside the data range on which they have been developed and validated. Thus, they can potentially provide insights that apply outside the limits of the system on which they were designed, predicting the results of a range of "what-if" scenarios (Duncan, 1975; Keating and Thorburn, 2018).

One class of process-based greenhouse models treats the greenhouse air as a "perfectly stirred tank" (Roy et al., 2002). In this approach the greenhouse air is treated as a uniform entity, where spatial variability is ignored and representative values of, e.g., air temperature are used. In some cases, the air is divided into compartments such as the air above and below a thermal screen (see example below), but still each compartment is assumed to be perfectly stirred. Furthermore, under this approach the greenhouse is often assumed (sometimes implicitly) to be infinitely large (e.g., De Zwart, 1993). One consequence of this approach is that the air is assumed not to be influenced by the side walls of the greenhouse.

Another class of models uses computational fluid dynamics (CFD) to describe the movement of air within the space of the greenhouse (Boulard et al., 2002). This method, which is considerably more complex and computationally intensive than the perfectly stirred tank approach, allows to describe heterogenous attributes of the greenhouse air and their change through space and time. A review on the possibilities and challenges of CFD in greenhouse modelling was given by Norton et al. (2007), and more recent advances were listed by Choab et al. (2019). Nevertheless, the heavy computational requirements of CFD models still limit their applicability, and a middle ground may be found by combining them with perfectly stirred tank approaches (Piscia et al., 2015).

Some greenhouse models are developed using building energy simulation programs such as EnergyPlus or TRNSYS (Choab et al., 2019). These programs were designed to simulate the energy demand of buildings, and considerable modifications are needed to correctly apply them for greenhouses (Ahamed et al., 2020). In these platforms, models are constructed using pre-existing components available within the simulation program. While this could facilitate model development, it reduces model transparency, since understanding the inner workings of the model requires considerable knowledge of the simulation program that was used for its development.

In this study, we focus on process-based, perfectly stirred tank models of the greenhouse climate. This means that we focus on the indoor climate and the processes that influence it (Fig. 1). An essential component of the indoor climate is the air, but other components (e.g., crop temperature, floor temperature) may also be included. Models that describe exclusively the control system (e.g., the boiler, cogenerator, heat storage) or exclusively the crop (yield models), are outside the scope of this study. Nevertheless, processes that influence the indoor climate (including crop processes such as photosynthesis and transpiration) are reviewed here. Since crop yield is the most important component of the greenhouse system, and in fact, the reason for its existence, we also survey how this component was considered whenever it was included.

2.2. Objectives of process-based greenhouse climate modelling

As mentioned earlier, process-based models are designed with the intention that they provide insights that lie outside the domain of knowledge and data that was used in their development (Duncan, 1975; Keating and Thorburn, 2018). The objectives and purposes of process-based greenhouse climate models can be classified into four categories: systems analysis, exploratory modelling, model-based control, and model-assisted design.

In systems analysis, a model is used to better understand or describe a particular greenhouse system. This approach often stems from a scientific, curiosity-driven, exploratory approach. Once the model is adequately described and understood, it can be used for other purposes such as model-based design and control. In systems analysis, methods such as sensitivity analysis can be used to reveal which components have a strong influence on the system. Here, care should be taken to be aware on what is actually being analyzed: the real-world system represented by the model, or the model itself, as a sensitivity analysis can uncover insights regarding both (e.g., Van Henten, 2003).

In exploratory modelling (also termed scenario analysis), the model is used to predict the results of untested scenarios. This analysis can point out directions for solving a problem or be used to narrow down a list of possible strategies or solutions which can then be tested in practice. For example, De Zwart (1996) used a model to find the most promising energy saving methods out of a predefined list.

Model-based control uses models to apply methods such as model predictive control or optimal control on the greenhouse climate (e.g., Katzin et al., 2020a; Kuijpers et al., 2021; Tap, 2000; Van Henten, 2003; Van Henten et al., 1997; Van Ooteghem, 2007; Van Straten et al., 2010). While this line of research generates meaningful insights regarding greenhouse climate control, it is rarely realized in commercial greenhouse practice (Van Beveren et al., 2015b).

Lastly, model-assisted design is a form of exploratory modelling used for the design of greenhouse systems. It may include scenario analysis or more sophisticated methods. For example, Vanthoor (2011) presented a model and an optimization method which was used to find an optimal design (based on model predictions) for a given location and situation.

2.3. General structure of process-based greenhouse climate models

In this section, we describe a general structure that is common in all process-based greenhouse climate models. At the same time, we outline the range of different approaches that are found between models. This section summarizes observations from several sources describing greenhouse models, with a wide range of complexity (De Zwart, 1996; Stanghellini et al., 2019; Van Henten, 1994; Van Straten et al., 2010).

The indoor climate may be described by one or more of the following attributes: temperature, humidity, CO_2 concentration, and light. A general way to model the temperature, humidity, and CO_2 concentration is by considering balances: an energy balance, a water vapor balance, and a CO_2 balance, but not all greenhouse climate models describe all three balances: some focus only on energy, or only on energy and water. For each of these balances, incoming and outgoing flows are identified, and the difference between the incoming and outgoing flows is the net change in each attribute. A set of equations that describes these net changes is:

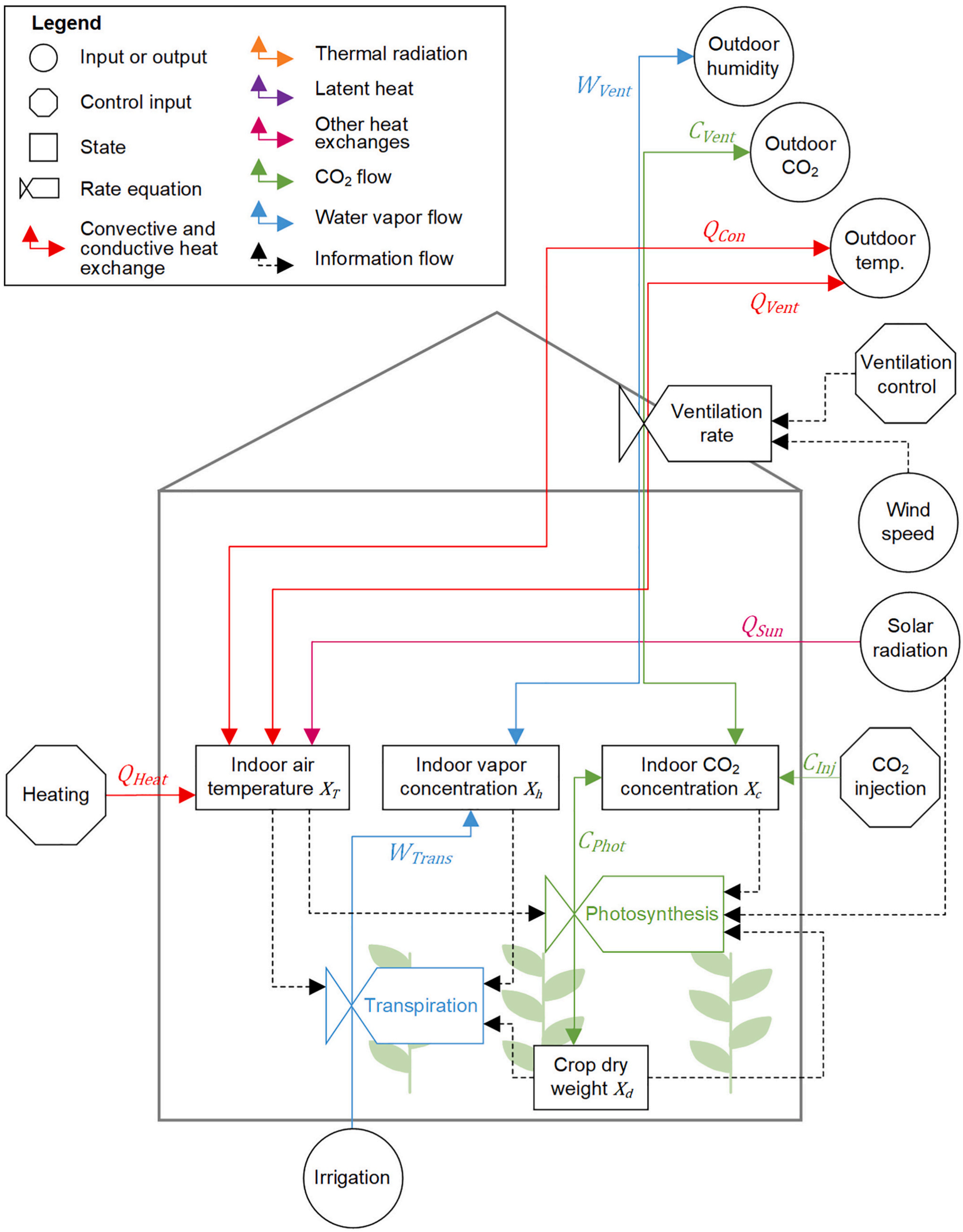


Fig. 2. Scheme of the Van Henten model (Eq. 1, Eq. 2) (Van Henten, 1994, 2003), based on the Forrester diagram conventions (Forrester, 1961; see also Haefner, 2005). Mass and energy flows are indicated by solid lines, information flows are indicated by dashed lines (see legend). Valves placed over solid lines indicate rate equations that influence the rate of the flow passing through the valve. Information flows indicate the influence of an input or a state on a rate of flow. For example, photosynthesis is influenced by solar radiation, crop dry weight, indoor air temperature and indoor CO_2 concentration. Photosynthesis in turn influences the rate of CO_2 flow from the indoor air to the crop. Arrows indicate which objects act as sources, sinks, or both. For example, the outdoor air may be a source or a sink of water vapor, but irrigation is only a source.

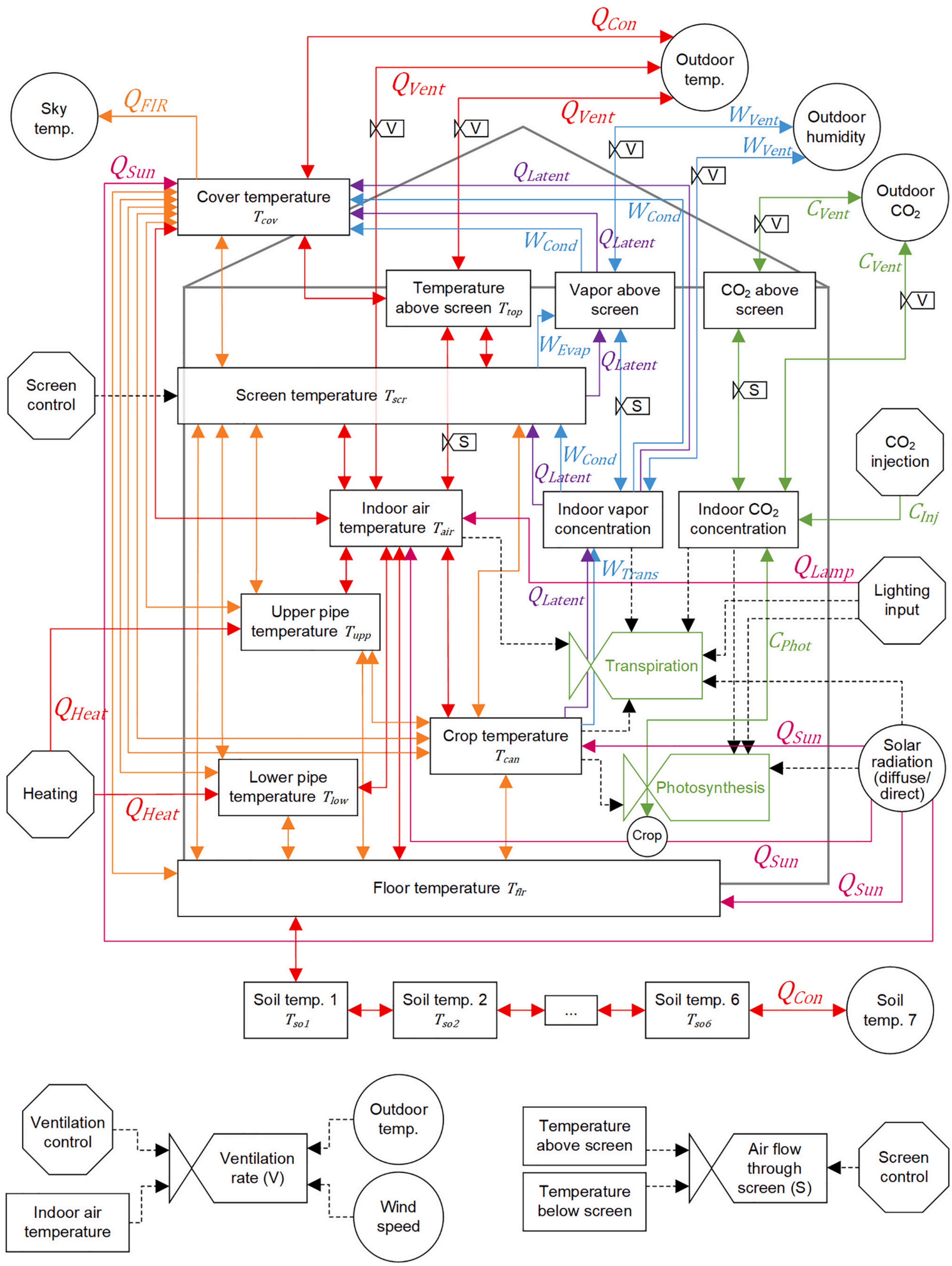


Fig. 3. Scheme of the De Zwart model (De Zwart, 1996) with its mass and energy flows (Eq. 1, Eq. 3). Influences on ventilation rate and air flow through screen are depicted below; their influence on other flows are indicated by valves labelled by *V* and *S*, respectively. See Fig. 2 for legend and further explanation of the diagram conventions. The photosynthesis rate influences the flow of CO_2 from the indoor air to the crop. CO_2 absorbed by the crop is an output of the greenhouse model which is in turn used as an input for a crop model. To simplify the figure, exchanges of latent heat Q_{Latent} are shown together with the accompanying change of phase of water W_{Trans}, W_{Cond}, or W_{Evap}. These processes simultaneously influence both the energy balance (a temperature of an object) as well as the water vapor balance (a vapor concentration of an object). For example, condensation of vapor from the indoor air onto the screen influences both the indoor vapor concentration (W_{Cond}) as well as the screen temperature (Q_{Latent}).

$$\begin{aligned} \frac{dE}{dt} &= Q_{Sun} + Q_{Heat} + Q_{Lamp} - Q_{Vent} - Q_{Latent} - Q_{Con} - Q_{FIR} - Q_{Cool} && (\mathrm{J\ m^{-2}\ s^{-1} = W\ m^{-2}}) \\ \frac{dM_W}{dt} &= W_{Trans} + W_{Evap} + W_{Hum} - W_{Cond} - W_{Vent} - W_{Dehum} && (\mathrm{kg\ \{water\ vapor\}\ m^{-2}\ s^{-1}}) \\ \frac{dM_C}{dt} &= C_{Inj} - C_{Phot} - C_{Vent} && (\mathrm{kg\ \{CO_2\}\ m^{-2}\ s^{-1}}) \end{aligned} \tag{1}$$

Here, each line represents a balance. The first line represents the energy balance, where $\frac{dE}{dt}$ is the net change of energy in the greenhouse, with t representing a time unit (in this case seconds), and E expressed in J m^{-2}. Expressions on the right-hand side of the equation are net flows which may be positive (adding energy, i.e., heating the greenhouse), negative (cooling the greenhouse), or zero. The sign in front of each expression in Eq. 1 indicates what is the typical direction of each flow: the typical incoming energy flows are Q_{Sun}, heating from the sun; Q_{Heat}, heat from the heating system; and Q_{Lamps}, heat emitted by lamps. The typical outgoing energy flows are Q_{Vent}, exchange of air through ventilation; Q_{Latent}, conversion from sensible to latent heat; Q_{Con}, convective and conductive exchanges with the outside; Q_{FIR}, thermal (far infrared) radiation; and Q_{Cool}, heat extracted by cooling mechanisms.

The second line represents the water vapor balance, with $\frac{dM_W}{dt}$ the net change of water vapor mass in the greenhouse. The typical incoming flows are W_{Trans}, crop transpiration; W_{Evap}, water evaporation from the soil or other surfaces; and W_{Hum}, which includes humidity added by control mechanisms such as fogging or pad and fan cooling. The typical outgoing flows are W_{Cond}, condensation of vapor on cold surfaces; W_{Vent}, vapor exchange through ventilation; and W_{Dehum}, vapor extracted by dehumidification mechanisms. Water vapor released by crop transpiration originates from irrigation, which is typically assumed to be supplied in a sufficient rate such that the water availability does not reduce transpiration.

The third line represents the CO_2 balance, where $\frac{dM_C}{dt}$ is the net change of CO_2 mass in the air. The typical incoming flow is C_{Inj}, enrichment of the air by CO_2 injection; the typical outgoing flows are C_{Phot}, crop net photosynthesis; and C_{Vent}, CO_2 exchange through ventilation.

Some of the flows above may act both as incoming and outgoing flows. For example, when C_{Vent} is positive it represents an outgoing flow, losses of CO_2 from the system through ventilation. This is the common case when the indoor CO_2 concentration is higher than the outdoor. However, C_{Vent} may also be negative, for instance, if the indoor CO_2 concentration is lower than the outdoor. In this case the expression $-C_{Vent}$ in Eq. 1 will be positive and represent an incoming flow of CO_2 to the system.

While Eq. 1 describes the greenhouse balances as differential equations, not all process-based greenhouse climate models describe or simulate these balances in this way. For example, the use of discrete-time difference equations is common (Lopez-Cruz et al., 2018). Furthermore, as can be seen in Fig. 1, many of the greenhouse components are interdependent: for example, crop transpiration and photosynthesis are influenced by the indoor climate, which is in turn influenced by crop transpiration and photosynthesis. Therefore, the model may need to be solved iteratively. Another approach is to assume that the entire system is in steady state, i.e., that $\frac{dE}{dt} = 0$, $\frac{dM_W}{dt} = 0$, $\frac{dM_C}{dt} = 0$. Using this approach allows to model all but one of the components in each line of Eq. 1, and calculate the last component based on the steady state assumption.

Light is an important attribute of the indoor climate of the greenhouse. In particular, the amount of photosynthetically active radiation (PAR) in the greenhouse may be used as an input to a crop model in order to estimate crop growth and photosynthesis, and the amount of short wave and/or long wave radiation may be used as an input for a transpiration model (Katsoulas and Stanghellini, 2019). The amount of available light in the greenhouse is a sum of the light originating from the sun and from lamps. Light from the sun inside the greenhouse is typically a product of the solar radiation outside the greenhouse and the greenhouse transmissivity, a unitless factor which describes what fraction of the outdoor radiation penetrates into the greenhouse. Light from the lamps is typically a factor of the energy provided to the lamps and the lamp's photosynthetic photon efficacy (PPE), which is expressed in μmol of photons of PAR light per J of energy input (Nelson and Bugbee, 2014).

2.3.1. Example1: The Van Henten model

A concrete example is the differential equations based model of Van Henten (1994, 2003), summarized here and in Fig. 2 using notation from Eq. 1:

$$\begin{aligned} \frac{dX_T}{dt} &= \frac{1}{c_{cap,q}}(Q_{Sun} + Q_{Heat} - Q_{Vent} - Q_{Con}) && (^\circ\mathrm{C\ s^{-1}}) \\ \frac{dX_h}{dt} &= \frac{1}{c_{cap,h}}(W_{Trans} - W_{Vent}) && (\mathrm{kg\ \{water\ vapor\}\ m^{-2}\ s^{-1}}) \\ \frac{dX_c}{dt} &= \frac{1}{c_{cap,c}}(C_{Inj} - C_{Phot} - C_{Vent}) && (\mathrm{kg\ \{CO_2\}\ m^{-2}\ s^{-1}}) \\ \frac{dX_d}{dt} &= f(X_T, X_C, X_d, V_{rad}) && (\mathrm{kg\ \{dry\ weight\}\ m^{-2}\ s^{-1}}) \\ C_{Phot} &= g(X_T, X_c, X_d, V_{rad}) && (\mathrm{kg\ \{CO_2\}\ m^{-2}\ s^{-1}}) \\ W_{Trans} &= h(X_T, X_h, X_d) && (\mathrm{kg\ \{water\ vapor\}\ m^{-2}\ s^{-1}}) \end{aligned} \tag{2}$$

This model is composed of 4 states described by 4 differential equations. Three of these states correspond to the balances of Eq. 1: the indoor temperature X_T (°C), the indoor vapor concentration X_h (kg {water vapor} m^{-3}), and the indoor CO_2 concentration X_c (kg {CO_2} m^{-3}), defined by equations corresponding to the balances E, M_W, and M_C of Eq. 1. The parameters $c_{cap,q}$, $c_{cap,h}$, $c_{cap,c}$ and the functions $f(X_T, X_C, X_d, V_{rad})$, $g(X_T, X_C, X_d, V_{rad})$, and $h(X_T, X_h, X_d)$ are described in Van Henten (1994, 2003). Several components mentioned in Eq. 1 are neglected in this model. At the same time, the model describes a state X_d representing the dry weight of the crop in the greenhouse (kg {dry weight} m^{-2}). This state, governed by the equation f whose definition is excluded here, provides additional information about the greenhouse system but it is not part of the climate balances. Nevertheless, the crop dry weight state X_d influences the photosynthesis and transpiration flows C_{Phot} and W_{Trans} (given here as functions g and h), which are part of the greenhouse climate system.

2.3.2. Example 2: The De Zwart model (KASPRO)

In order to illustrate the range of models that are represented by Eq. 1, another example (De Zwart, 1996) is given in Fig. 3. The De Zwart model (also known as KASPRO), developed around the same time and place as the Van Henten model, is remarkably more elaborate. It includes nearly all components listed in Eq. 1, with several of them further decomposed to smaller subcomponents. For example, Q_{Sun} is divided into diffuse and direct radiation from the sun and is composed of solar radiation heating the greenhouse floor, air, crop, and cover. Using the notation of the De Zwart model, the various components of the energy balance are defined by:

$$
\begin{aligned}
&Q_{Sun} = P_{SunCov} + P_{SunAir} + P_{VISCan} + P_{NIRCan} + P_{VISFlr} + P_{NIRFlr} && (\mathrm{W\,m^{-2}})\\
&Q_{Heat} = H_{BoilUpp} + H_{BoilLow} && (\mathrm{W\,m^{-2}})\\
&Q_{Lamp} = P_{AluAir} && (\mathrm{W\,m^{-2}})\\
&Q_{Vent} = H_{TopOut} + H_{AirOut} && (\mathrm{W\,m^{-2}})\\
&Q_{Latent} = L_{CanAir} + L_{ScrTop} - L_{AirScr} - L_{TopCov} - L_{AirCov} && (\mathrm{W\,m^{-2}})\\
&Q_{Con} = H_{CovOut} && (\mathrm{W\,m^{-2}})\\
&Q_{FIR} = R_{CovSky} && (\mathrm{W\,m^{-2}})
\end{aligned} \tag{3}
$$

Here, P is net shortwave radiation, H is net convection or conduction, L is net latent energy, and R is net thermal radiation. The subscripts indicate the origin and target of the net energy flow: for example, H_{CovOut} represents net energy exchange by convection from the greenhouse cover to the outside air. When H_{CovOut} is positive, the net energy transfer is from the cover to the outside air, cooling the greenhouse; when H_{CovOut} is negative, the net energy transfer is from the outside air to the cover, heating the greenhouse.. Note that P_{VISCan} and P_{NIRCan} are denoted by a single line in Fig. 3, and similarly for P_{VISFlr} and P_{NIRFlr}. Similar equations as in Eq. 3 can be constructed for the water and CO_2 balances.

The De Zwart model is made up of 14 states that are defined using ordinary differential equations. These states are: the vapor pressure of the air below the screen, the CO_2 concentration of the air below the screen, and the temperatures of the cover, air below the screen, crop, upper heating net, lower heating net, floor, and 6 soil layers. Four additional variables are calculated using algebraic equations. These variables are: the vapor pressure of the air above the screen, the CO_2 concentration of the air above the screen, the temperature of air above the screen, and the temperature of the screen (see Eq. 4, below). As in the case of the Van Henten model, the states serve two purposes: first, they add detail to the simulation, providing descriptions for the temperatures of the cover, air, canopy, etc. Second, these details are used to calculate the inflows and outflows of the general balance equations (Eq. 3). For example, the net flow of thermal radiation Q_{FIR} is defined as the thermal radiation from the cover to the sky R_{CovSky}. This value depends on the cover temperature T_{Cov}, as will be illustrated in the next section.

To give more concrete detail, some of the equations concerning the energy balance in the De Zwart model are:

$$
\begin{aligned}
&\frac{dT_{cov}}{dt} = \frac{1}{\rho_{cov} c_{p,cov} V_{cov}} \left(P_{SunCov} + H_{TopCov} + H_{AirCov} + R_{FlrCov} + R_{ScrCov} + R_{UppCov} + R_{LowCov} + R_{CanCov} + L_{TopCov} + L_{AirCov} - H_{CovOut} - R_{CovSky}\right) && (^\circ\mathrm{C\,s^{-1}})\\
&0 = H_{ScrTop} + H_{AirTop} - H_{TopCov} - H_{TopOut} && (^\circ\mathrm{C\,s^{-1}})\\
&0 = R_{FlrScr} + L_{AirScr} + R_{UppScr} + R_{LowScr} + H_{AirScr} + R_{CanScr} - H_{ScrTop} - L_{ScrTop} - R_{ScrCov} && (^\circ\mathrm{C\,s^{-1}})\\
&\frac{dT_{air}}{dt} = \frac{1}{\rho_{air} c_{p,air} V_{air}} \left(P_{AluAir} + P_{SunAir} + H_{UppAir} + H_{LowAir} + H_{CanAir} - H_{AirFlr} - H_{AirTop} - H_{AirScr} - H_{AirOut} - H_{AirCov}\right) && (^\circ\mathrm{C\,s^{-1}})\\
&\frac{dT_{can}}{dt} = \frac{1}{cap_{leaf} LAI} \left(R_{UppCan} + R_{LowCan} + P_{VISCan} + P_{NIRCan} - H_{CanAir} - R_{CanCov} - R_{CanScr} - R_{CanFlr} - L_{CanAir}\right) && (^\circ\mathrm{C\,s^{-1}})\\
&\frac{dT_{flr}}{dt} = \frac{1}{\rho_{flr} c_{p,flr} V_{flr}} \left(R_{LowFlr} + R_{UppFlr} + H_{AirFlr} + R_{CanFlr} + P_{VISFlr} + P_{NIRFlr} - H_{FlrSo1} - R_{FlrScr} - R_{FlrCov}\right) && (^\circ\mathrm{C\,s^{-1}})\\
&\frac{dT_{upp}}{dt} = \frac{1}{\rho_{upp} c_{p,upp} V_{upp}} \left(H_{BoilUpp} - R_{UppScr} - R_{UppCov} - H_{UppAir} - R_{UppCan} - R_{UppFlr}\right) && (^\circ\mathrm{C\,s^{-1}})\\
&\frac{dT_{low}}{dt} = \frac{1}{\rho_{low} c_{p,low} V_{low}} \left(H_{BoilLow} - R_{LowScr} + R_{LowCov} + H_{LowAir} + R_{LowCan} + R_{LowFlr}\right) && (^\circ\mathrm{C\,s^{-1}})\\
&\frac{dT_{so(i)}}{dt} = \frac{1}{th_{so(i)} \rho c_{p,soil}} \left(H_{So(i-1)So(i)} - H_{So(i)So(i+1)}\right) \quad i = 1,\ldots 6 && (^\circ\mathrm{C\,s^{-1}})
\end{aligned} \tag{4}
$$

Here, T is the temperature of an object in the greenhouse (°C), and ρ, c, V, Cap, $th_{so(i)}$, $\rho c_{p,\ soil}$ are model parameters. Subscripts (Cov, Top, Scr, etc.) are as described in Fig. 3. $H_{BoilUpp}$ and $H_{BoilLow}$ are energy flows from the boiler to the upper and lower heating nets. The De Zwart model includes elaborate sub-models to calculate these energy flows, which are outside the scope of this review.

2.4. Components of process-based greenhouse models

As illustrated by the examples in Section 2.3, a broad range of approaches is possible for modelling the greenhouse climate. These approaches can be classified on a spectrum between "simple" and "complex". Complex models include a larger number of processes and objects, and use mechanistic descriptions of processes that involve multiple influencing variables or inputs. Simpler models neglect some processes, use fewer objects, and summarize phenomena with descriptive functions, while maintaining an overall process-based model structure. Objects in this context are entities that are described by variables: objects of the energy balance are described by their temperature, objects of the water vapor balance are described by their vapor concentration, and objects of the CO_2 balance are described by their CO_2 concentration. For example, the Van Henten energy balance includes only two objects: indoor and outdoor air, and only 4 processes: solar radiation, heating pipes, convection and ventilation (Fig. 2, Eq. 2). The De Zwart energy balance has 17 objects, including soil layers and the sky temperature, and processes not considered by Van Henten such as thermal radiation (FIR) and conversion to latent heat (Fig. 3, Eq. 3, Eq. 4).

Besides the objects and processes included, models also vary in how each process is described. Table 1 lists simple and complex approaches that are used to describe some of the processes in Eq. 1. The following subsections provide further detail.

2.4.1. Solar radiation and energy from lamps

The heating input from the sun can be described as $Q_{Sun} = a_{Sun} I_{Sun}$ (W m^{-2}) with I_{Sun} (W m^{-2}) representing solar radiation from the sun and a_{Sun} (−) the fraction of global radiation that contributes to heating the greenhouse. Solar radiation I_{Sun} is typically given as an input to the model. This input may be a single value representing global radiation, or two values differentiating between direct and diffuse radiation. Solar radiation can further be decomposed into photosynthetically active radiation (PAR), which is used by the crop model to calculate photosynthesis, and other wavebands, such as near infrared radiation (NIR) or ultraviolet (UV) radiation which contribute to heating but not to photosynthesis. The coefficient a_{Sun} may be assumed constant, or depend on the location of the sun in the sky and the amount of diffuse and direct radiation. Note that the value of a_{Sun} can be different from greenhouse transmissivity, a measure of what fraction of the outdoor sunlight penetrates the greenhouse and reaches the canopy, which is used when estimating photosynthesis. Both a_{Sun} and greenhouse transmissivity can be wavelength-dependent.

Heating from the lamps can be described as $Q_{Lamp} = a_{Lamp} I_{Lamp}$ (W m^{-2}) where I_{Lamp} (W m^{-2}) is the energy input (electricity) provided to lamps and a_{Lamp} (−) is the fraction of this input that contributes to heating the greenhouse. As with solar radiation, a_{Lamp} may be assumed constant or be dependent on a sub-model describing the lamp output in terms of photosynthetically active radiation (PAR), near infrared radiation (NIR), thermal (far infrared) radiation (FIR), convective and

Table 1
Model components of process-based greenhouse models and the range of approaches used to describe them, from simple to complex approaches. A dash (–) indicates that no basic formula is commonly used.

Model component	Basic formula	Simple approaches	Complex approaches
Q_{Sun}, heating from the sun (W m^{-2})	$a_{Sun}I_{Sun}$	a_{Sun} is constant, I_{Sun} is global radiation given as input	a_{Sun} depends on location of sun and geometry of the greenhouse, I_{Sun} includes diffuse and direct radiation
Q_{Heat}, heating from the heating system (W m^{-2})	–	Value is given or calculated based on balance equation	Sub-model based on temperatures of pipes, water in boiler
Q_{Lamp}, heating from lamps (W m^{-2})	$a_{Lamp}I_{Lamp}$	a_{Lamp} is constant, I_{Lamp} is given as input	Lamp energy output divided into PAR, NIR, FIR, convection
Q_{Vent}, energy loss to ventilation (W m^{-2})	$vc(T_1 - T_2)$	Neglected, v is constant, or v is given as an input	v depends on window opening, wind speed and direction, indoor and outdoor temperature
Q_{Con}, convective and conductive heat exchange (W m^{-2})	$h(T_1 - T_2)$	Only 2 temperatures included representing indoor and outdoor, h assumed constant	multiple objects included, h depends on objects' temperatures, shapes, air movement
Q_{FIR}, thermal radiation (W m^{-2})	$F\varepsilon_1\varepsilon_2\sigma \cdot ((T_{1,K})^4 - (T_{2,K})^4)$	Neglected, or only radiation to the sky. Sky temperature depends on outdoor air temperature	Multiple objects included, F is variable, sky temperature (when included) depends on outdoor air temperature, humidity, cloud cover
Q_{Latent}, losses to latent heat (W m^{-2})	$L \cdot W_{Latent}$	Neglected	Includes crop transpiration, evaporation and condensation on multiple surfaces (soil, screens, cover)
W_{Trans}, crop transpiration (kg m^{-2} s^{-1})	–	Depends on radiation	Depends on leaf area index (LAI), vapor pressure deficit (VPD), stomatal response to radiation, CO_2 concentration, humidity, crop temperature
W_{Vent}, vapor loss through ventilation (kg m^{-2} s^{-1})	$v(V_1 - V_2)$	See Q_{Vent}	See Q_{Vent}
W_{Cond}, condensation and evaporation (kg m^{-2} s^{-1})	$\max\{0, g(V_{Air} - V_{Surface})\}$	Neglected	Condensation on multiple surfaces (screen, cover) included
C_{Inj}, CO_2 injection (kg m^{-2} s^{-1})	–	Given as input	Depends on availability of sources such as flue gas from boiler
C_{Vent}, CO_2 loss through ventilation (kg m^{-2} s^{-1})	$v(C_1 - C_2)$	See Q_{Vent}	See Q_{Vent}
C_{Phot}, Crop photosynthesis (kg m^{-2} s^{-1})	–	Depends on radiation	Depends on LAI, radiation, CO_2, temperature, crop developmental processes

conductive heating. The choice on how to model the lamps may also depend on which lamps are considered, e.g., incandescent lamps; fluorescent lamps; high-intensity discharge lamps such as high-pressure sodium (HPS) or metal-halide lamps; or light emitting diodes (LEDs). Naturally, for greenhouses without supplemental lighting this component is not incorporated in the model.

2.4.2. Ventilation

Energy lost through ventilation is typically represented by air exchanges between two bodies:

$$Q_{Vent} = vc(T_1 - T_2)\ \left(\mathrm{W\ m^{-2}}\right) \tag{5}$$

where T_1 and T_2 (°C) are the temperatures of the two bodies, c (J m^{-3} °C^{-1}) is the volumetric heat capacity of the air, and v (m^3 m^{-2} s^{-1}) is the rate of air exchange. In the simplest cases Q_{vent} is neglected or assumed constant. Alternatively (as in the Van Henten model), v is given as an input, T_1 is the indoor temperature, and T_2 is the outdoor temperature. In more complex models (as in the De Zwart model) several air exchanges are considered, modelled as in Eq. 5, and summed to constitute Q_{Vent}. A complex approach to modelling v takes into account factors such as the degree of opening of the windows; outdoor wind speed; temperature differences between indoor and outdoor air; the number, geometry, and location (roof, side wall) of the windows; and more. Other air exchanges in the greenhouse (e.g., between the air below and above a screen) can be modelled similarly.

The air exchange between indoor and outdoor air v is used similarly in the calculation of losses of water vapor and CO_2 through ventilation:

$$W_{Vent} = v(V_1 - V_2)\ \left(\mathrm{kg\ \{water\}\ m^{-2}\ s^{-1}}\right) \tag{6}$$

$$C_{Vent} = v(C_1 - C_2)\ \left(\mathrm{kg\ \{CO_2\}\ m^{-2}\ s^{-1}}\right) \tag{7}$$

where W_{Vent} (kg {water} m^{-2} s^{-1}) is the rate of water vapor loss to the outside, and V_1 and V_2 (kg {water} m^{-3}) are, respectively, the indoor and outdoor water vapor concentrations. Similarly, C_{Vent} (kg {CO_2} m^{-2} s^{-1}) is the rate of CO_2 loss to the outside, and C_1 and C_2 (kg {CO_2} m^{-3}) are the indoor and outdoor CO_2 concentrations.

2.4.3. Convection and conduction

Convection and conduction between two bodies are typically calculated according to Fourier's law:

$$Q_{Con} = h(T_1 - T_2)\ \left(\mathrm{W\ m^{-2}}\right) \tag{8}$$

where h (W °C^{-1} m^{-2}) is called the heat exchange coefficient and T_1 and T_2 (°C) are temperatures of the two bodies. Convection and conduction are quite different processes, but they are often lumped together in greenhouse models. For example, in convective exchanges the heat exchange coefficient h is often described by a non-linear function of the temperature difference $T_1 - T_2$, and may depend on other factors such as wind, although a simple approach assumes a constant h.

In greenhouse modelling, convection and conduction are often treated in a similar fashion primarily because these processes are spatiotemporal in nature, describing a transport of energy through space and time. In the framework of "perfectly stirred" homogenous models, this transport is reduced to a temporally dynamic process. In this sense, Eq. 8 can be seen as a first-order approximation of two partial differential equations that describe heat transport in space and time (see e.g., Van Mourik (2008)).

What T_1 and T_2 (°C) represent depends on the context. In simple cases, T_1 represents the greenhouse temperature, typically the greenhouse air, and T_2 is the temperature of the outside air. If conduction to the soil is included, a function as in Eq. 8 may be added where T_2 is the soil temperature.

A more complex approach looks explicitly at heat exchanges occurring on the greenhouse outer surface. In this case, T_1 represents the temperature of the greenhouse cover, which would require modelling this object. Conduction to the soil can include several soil layers, as in the De Zwart model (Fig. 3). Convection and conduction between other greenhouse objects (screens, lamps, the crop, heating pipes, and more)

Table 2
Overview of studies related to process-based greenhouse climate modelling, 2018–2020. Category indicates the category of the study. Development is the development status of the model used in the study. Greenhouse type: PE: polyethylene, CSG: Chinese solar greenhouse. Equipment: B: boiler, BS: blackout screen, C: cooling, CHP: cogenerator, CO_2: CO_2 injection, DAH: direct air heating, FG: fogging, FN: fans, GP: grow-pipes, H: heating, HPS: high-pressure sodium lamps, HS: heat storage, HU: humidification, L: lamps (no lamp type specified), LED: light-emitting diodes, MHL: metal halide lamps, PV: photovoltaic cells, P&F: pad and fan cooling, TS: thermal screen. All models include ventilation and all CSG models include a thermal blanket and heat storage in a wall. Crop: None: no crop was present in the greenhouse. n/a: information was not available. See Section 3.1 for more details.

Reference	Category	Purpose	Greenhouse type	Equipment	Crop	Development
Abbes et al. (2019)	Control	Develop a greenhouse model for North African context to help control microclimate	PE tunnel	–	None	Extension
Ahamed et al. (2018a)	Exploratory	Develop a model for designing and estimating heating demands of CSGs	CSG	CO_2, FN, H, L	Tomato	Extension
Ahamed et al. (2018c)	Design	Design an energy efficient greenhouse	Double-layer PE	CO_2, FN, L, TS	Tomato	Reuse
Ahamed et al. (2018d)	Analysis	Estimate heating demands of CSG	CSG double layer PE	CO_2, FN, H, L	Tomato	Reuse
Ahamed et al. (2020)	Analysis	Develop a TRNSYS based model for CSGs	CSG, glass cover	CO_2, FN, H, L	n/a	Translation
Alinejad et al. (2020)	Design	Asses an adjustable PV blind system for greenhouses	Multi-span flat arch PE	FN, H, P&F, PV, TS	Rose	New
Baglivo et al. (2020)	Analysis	Develop a TRNSYS based model for greenhouses	Venlo	C, H, HPS	Chrysanthemum	New
Chen et al. (2019b)	Design	Design a CSG	CSG	–	n/a	New
Chen et al. (2019a)	Design	Evaluate placement of PV cells on a greenhouse roof	Venlo	PV	Vriesea	Extension
De Ridder et al. (2020)	Calibration	Propose a method for model calibration	Venlo	H, HPS, LED, TS	Cucumber	New
Esmaeli and Roshandel (2020)	Design	Optimize the design of a CSG	CSG	–	Various	New
Gharghory (2020)	Calibration	Use a deep network to predict greenhouse indoor climate	n/a	FG, H	n/a	Reuse
Golzar et al. (2018)	Design	Develop a greenhouse model that includes energy demand and yield in order to optimize greenhouse design	Venlo	CO_2, H, HU, MHL	Tomato	New
Golzar et al. (2019)	Analysis	Investigate the most important drivers for environmental impacts of greenhouses	Venlo	CO_2, H, HU, MHL	Tomato	Reuse
Hemming et al. (2019b)	Exploratory	Compare greenhouse control strategies under different settings	Venlo	CO_2, HPS, TS	Cucumber	Extension
Jomaa et al. (2019)	Control	Use fuzzy logic to control the greenhouse temperature	n/a	FG, H	n/a	Reuse
Katzin et al. (2020b)	Exploratory	Design a greenhouse model to predict the implications of changing the greenhouse lighting system	Venlo	BS, CO_2, H, HPS, LED, TS	Tomato	Extension
Lammari et al. (2020)	Control	Perform model calibration and setpoint tracking using proportional integral sliding mode controllers	Multi-span arch, PE	FG, H	Tomato	Reuse
Ma et al. (2019)	Control	Predict the microclimate to achieve climate homogeneity with a conveyor belt system	Venlo	HPS, P&F	n/a	New
Mohamed and Hameed (2018)	Control	Use an adaptive neuro fuzzy interface system to control a greenhouse	n/a	FG, H	None	Reuse
Mohammadi et al. (2020)	Analysis	Develop a model for a semi-solar greenhouse	CSG, glass cover	–	Cabbage	New
Pérez-González et al. (2018)	Calibration	Apply particle swarm optimization and differential evolution to parametrize a greenhouse model	Single span arch	FG, H	None	Extension
Rasheed et al. (2019)	Design	Propose a reliable greenhouse model by using TRNSYS, with a focus on thermal screens	Gambrel roof, double PE	H, TS	None	New
Righini et al. (2020)	Exploratory	Extend a greenhouse model by adding lamps, heat harvesting and test how energy can be saved	Venlo	CO_2, GP, H, HPS, HS, LED, TS	Tomato	Extension
Seginer et al. (2020b)	Control	Evaluate the advantage of expanding the indoor climate bounds	Venlo	B, CHP, HS	Tomato	Extension
Sethi (2019)	Design	Develop a model for an asymmetric overlap roof shape (AORS) greenhouse	PE	FG, FN	Tomato	New
Su et al. (2018)	Control	Apply optimal control based on adaptive dynamic programming to save energy	Venlo	DAH, F	Tomato	Extension
Subin et al. (2020)	Control	Implement fuzzy proportional-integral-derivative controllers to control temperature and humidity	n/a	FG	n/a	Reuse
Xu et al. (2018a)	Control	Apply adaptive two timestep receding horizon optimal control (TTRHOC) on a greenhouse	Venlo	CO_2, H	Lettuce	Reuse
Xu et al. (2018b)	Control	Realize economic optimization in CSG using TTRHOC	CSG	CO_2, H, LED	Lettuce	Extension
Xu et al. (2019)	Control	Quantify the benefits of TTRHOC on a greenhouse with LEDs	Venlo	CO_2, H, LED	Lettuce	Extension
Zhang et al. (2020)	Analysis	Develop a model with dynamic cover absorbance and transmittance factors	Venlo	–	None	New

are modelled similarly.

2.4.4. Thermal radiation

Thermal radiation between two objects, also called long wave radiation or far infrared (FIR) radiation, is modelled according to the Stefan-Boltzmann law:

$$Q_{FIR} = F\varepsilon_1\varepsilon_2\sigma\left(\left(T_{1,K}\right)^4 - \left(T_{2,K}\right)^4\right)\ \left(\mathrm{W\ m^{-2}}\right) \tag{9}$$

where F (−), called the view factor, expresses how visible the two objects are to each other; ε_1 and ε_2 (−) are the emissivities of the two objects, which are a property of the bodies' material; $\sigma = 5.67 \cdot 10^{-8}\ \mathrm{W\ m^{-2}\ K^{-4}}$ is the Stefan-Boltzmann constant; and $T_{1,K}$ and $T_{2,K}$ (K) are temperatures in kelvin of the two objects.

Air emits very little thermal radiation, so using indoor air temperature as $T_{1,K}$ and the outdoor air temperature as $T_{2,K}$ in Eq. 9 is typically insufficient to calculate the thermal radiation losses of the greenhouse system. The effective sky temperature (or simply sky temperature),

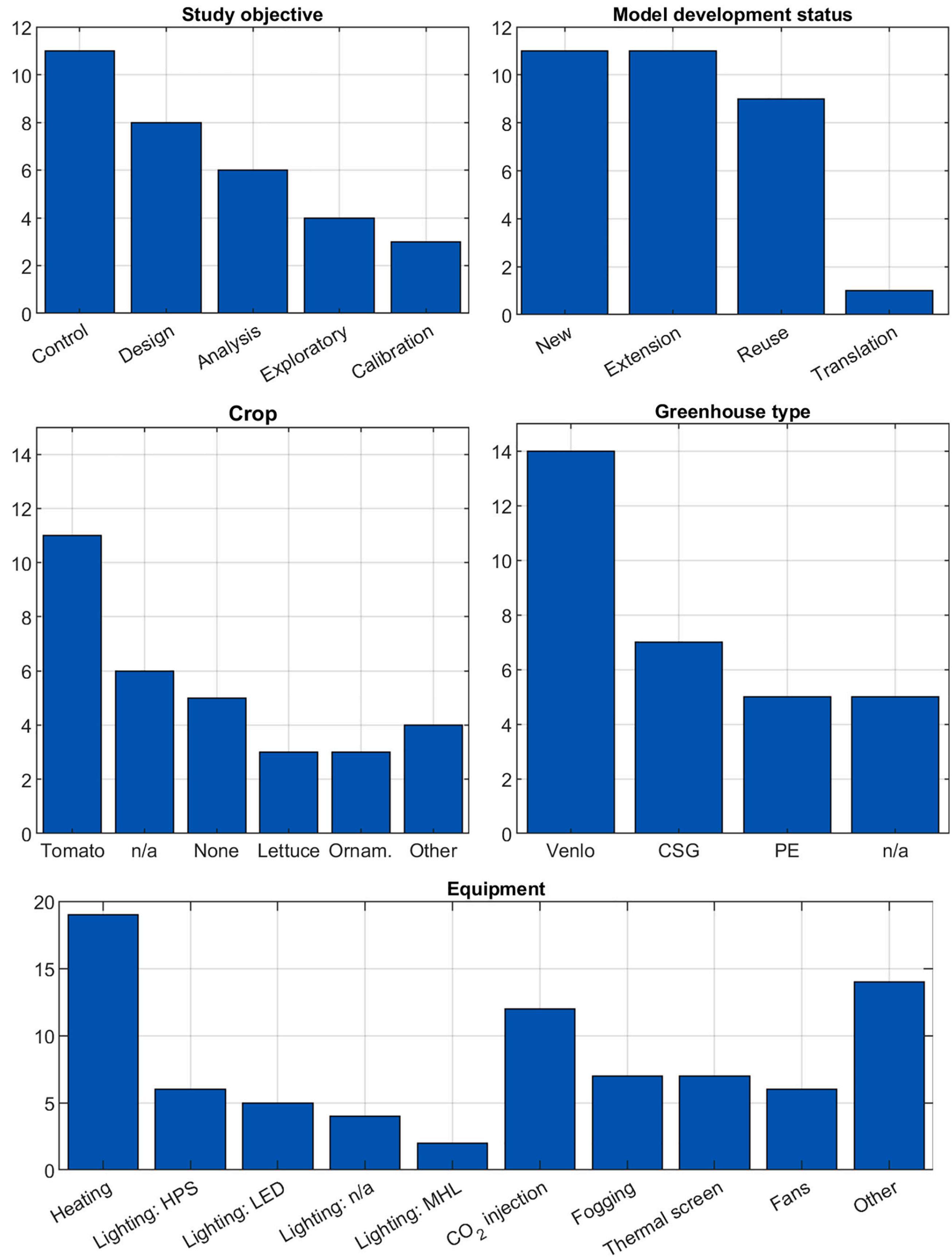


Fig. 4. Classification of studies related to process-based greenhouse climate modelling. Ornam: ornamental crops. CSG: Chinese solar greenhouse. PE: polyethylene. HPS: high-pressure sodium lamps. LED: light-emitting diodes. MHL: metal halide lamps. n/a: information was not available.

Table 3
Decomposition of greenhouse models, including model objective, number of objects considered in convective and radiative exchanges, variables influencing selected processes, and origins of model components. **Color code:** Blue: model extension, components that were changed during model extension based on previous sources. Green: new model or new model component. Red: model reuse. Yellow: component not included in the model. **Model objective:** Ctrl: climate control, Expl: exploratory modelling, Calib: calibration, Analys: system analysis. **Greenhouse type:** PE: polyethylene, CSG: Chinese solar greenhouse, Ven: Venlo. **Development:** Ex: extension, RE: reuse. **Model decomposition:** C: calculated based on other components, F: only fogging included, G: given as input, O: constant, N: no heating contribution, New: new model or component, ∝: proportional to input, ×: component excluded, ✓: component included. **Lamp type:** n/a: not specified, H: high-pressure sodium, L: LED, M: metal halide. **Influence of climate variables:** Ci: indoor CO_2 concentration, DW: crop dry weight, Hi: indoor humidity, Ho: outdoor humidity, LAI: leaf area index, n/a: information not available, R: radiation, Tc: crop temperature, Ti: indoor temperature, To: outdoor temperature, V: ventilation control, W: wind. [−] model simplification. [+] model extension. **References:** [1] Abbes et al. (2010). [2] Ahamed et al. (2018b). [3] Jolliet et al. (1991). [4] J. Chen et al. (2016). [5] J. Chen et al. (2015). [6] Pasgianos et al. (2003). [7] De Zwart (1996). [8] Jones et al. (1999). [9] Bontsema et al. (2007). [10] Stanghellini et al. (2012). [11] Marcelis et al. (2009). [12] Blasco et al. (2007) [13] Vanthoor et al. (2011b). [14] Vanthoor et al. (2011a). [15] Lammari et al. (2012). [16] Albright et al. (2001). [17] Van Ooteghem (2007). [18] Stanghellini (1987). [19] Hasni et al. (2011) [20] Seginer et al. (2018). [21] Seginer et al. (2020a). [22] Tiwari and Goyal (1998). [23] Tap (2000). [24] Roy et al. (2002). [25] Goudriaan and Van Laar (1993). [26] Van Henten (2003).

Reference	Model objective	Greenhouse type	Development	Heat from sun	Heating system	Heat from lighting (lamp type)	Thermal radiation (# of objects)	Convection (# of objects)	Ventilation	Latent heat	Leaf area index (LAI)	Transpiration	Evaporation, condensation (# of objects)	Net photo-synthesis	Yield model
Abbes et al. (2019)	Ctrl	PE	Ex [1]	[1]	✗	✗	4	8 [1]	O	✓	O	Hi, LAI, R, Tc, Ti [1]	3	✗	✗
Ahamed et al. (2018a, 2018d)	Expl	CSG	Ex [2]	[2]	C	∝ (n/a)	3 [2]	5	Ti, To, W [3]	✓	O	Hi, LAI, R, Ti, W [2]	✗	✗	✗
Ahamed et al. (2018b, 2018c)	Design	PE	New	New	C	∝ (n/a)	3 [2]	3 [2]	O	✓	O	Hi, LAI, R, Ti, W [2]	✗	✗	✗
J. Chen et al. (2019)	Design	Ven	Ex [4]	New	✗	✗	3	6	✗	✗	✗	✗	✗	✗	✗
De Ridder et al. (2020)	Calib	Ven	New	∝	C	∝ (H,L)	✗	5	V	✓	✗	Hi, Ho	✗	✗	✗
Esmaeli & Roshandel (2020, 2017)	Design	CSG	New	∝	✗	✗	✗	9	O	✓	n/a	Hi, LAI, R, Ti [5]	✗	✗	✗
Gharghory (2020)	Calib	n/a	Re [6]	G	✗	✗	✗	2 [6]	G [6]	F	✗	R [6]	✗	✗	✗
Golzar et al. (2018, 2019)	Design	Ven	New	∝	C	∝ (M)	2	2	Ti, To, V, W [7]	✓	[8]	Hi, LAI, R, Ti [9]	1	R, Ci [10]	[8]
Hemming et al. (2019b)	Expl	Ven	Ex [7]	[7]	[7]	∝ (H) [7]	7 [7]	16 [7]	Ti, To, V, W [7]	✓	n/a	Ci, Hi, LAI, R, Tc, Ti [7]	2	n/a [11]	[11+]
Jomaa et al. (2019)	Ctrl	n/a	Re [12]	∝ [12]	G	✗	✗	4 [12]	Ti, To, V [12]	✓	O	Hi, LAI, R, Ti [12]	✗	✗	✗
Katzin et al. (2020b)	Expl	Ven	Ex [13]	∝	C, G	New (H, L)	11 [13+]	18 [13+]	Ti, To, V, W [13]	✓	O	Ci, Hi, LAI, R, Tc, Ti [13]	3	Ci, LAI, R, Tc [14]	[14]
Lammari et al. (2020)	Ctrl	PE	Re [15]	∝	G	✗	✗	4 [15]	O [15]	✓	✗	Hi, R, Ti [15]	✗	✗	✗
Mohamed & Hameed (2018)	Ctrl	n/a	Re [16]	G	G	✗	✗	2 [16]	G [16]	F	✗	Hi, R [16]	✗	✗	✗
Mohammadi et al. (2020)	Analys	CSG	New	∝	✗	✗	5	6 [17]	W [17-]	✓	O	Hi, LAI, R, Tc, Ti [18]	2	✗	✗
Pérez-González et al. (2018)	Calib	PE	Ex [19]	∝	G	✗	✗	3 [19]	O [19]	✓	✗	Hi, R, Ti [19+]	✗	✗	✗
Righini et al. (2020)	Expl	Ven	Ex [13]	∝	G	∝ (H, L)	10 [13+]	17 [13+]	Ti, To, V,W [13]	✓	[14]	Ci, Hi, LAI, R, Tc, Ti [13]	2	Ci, LAI, R, Tc [14]	[14]
Seginer et al. (2020b)	Ctrl	Ven	Ex [20]	∝	G	✗	✗	2	G [20]	✓	O	R [21]	✗	Ci, R, Ti [20]	∝DW
Sethi (2019)	Design	PE	New	New	✗	✗	4	4	G	✓	✗	Ti, Tc [22]	✗	✗	✗
Su et al. (2018)	Ctrl	Ven	Ex [23]	∝	G	✗	✗	3	V, W [24-]	✓	O	Hi, R, Ti [23]	1	Ci, LAI, R, Ti [25]	✗
Subin et al. (2020)	Ctrl	n/a	Re [6]	G	✗	✗	✗	2 [6]	G [6]	F	✗	R [6]	✗	✗	✗
Xu et al. (2018a)	Ctrl	Ven	Re [26]	∝	G	✗	✗	2 [26]	G	✗	∝ DW	Hi, LAI, Ti [26]	✗	Ci, LAI, R, Ti [26]	∝DW
Xu et al. (2018b)	Ctrl	CSG	Ex [26]	∝	G	N (L)	✗	3 [26+]	G	✗	∝ DW	Hi, LAI, Ti [26]	✗	Ci, LAI, R, Ti [26]	∝DW
Xu et al. (2019)	Ctrl	Ven	Ex [26]	∝	G	N (L)	✗	2 [26]	G	✗	∝ DW	Hi, LAI, Ti [26]	✗	Ci, LAI, R, Ti [26]	∝DW
Zhang et al. (2020)	Analys	Ven	New	New	✗	✗	3	10	✗	✗	✗	✗	✗	✗	✗

which is a function of the thermal radiation emitted from the sky towards the earth, is typically used for $T_{2,K}$ when calculating the radiative losses of buildings (Evangelisti et al., 2019), including greenhouses. Sky temperature may be given as an input, or calculated based on outdoor air temperature, humidity, and cloud cover. As in the case of convection, the cover temperature is often used for $T_{1,K}$. Thermal radiation exchange between greenhouse objects, such as the greenhouse cover, the crop, and the soil, are modelled similarly.

2.4.5. Energy losses to latent heat

An important component of the energy balance is conversion of sensible to latent heat. This is described as:

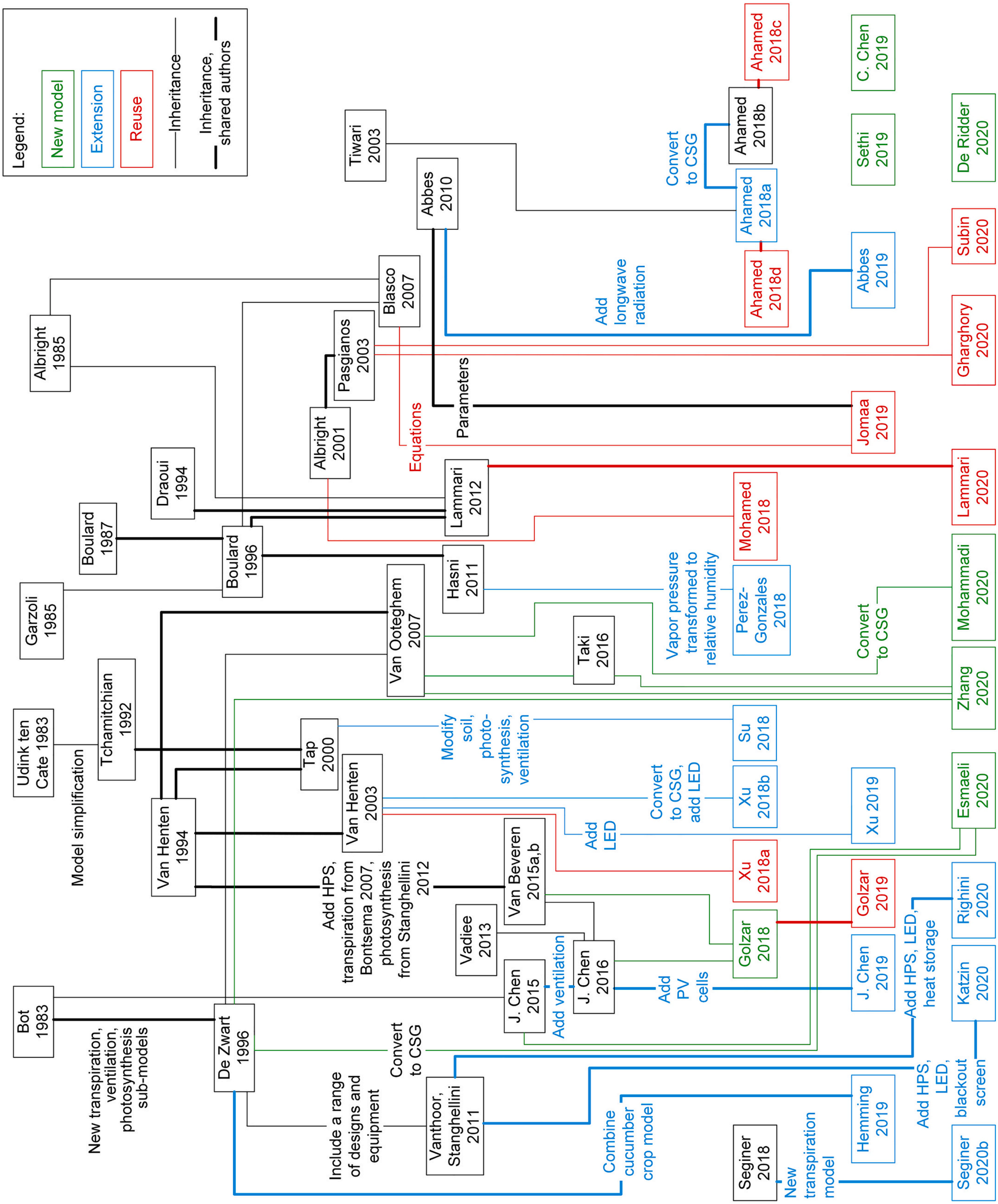


Fig. 5. Inheritance chart of recently published greenhouse modelling studies and the models on which they are based. Studies are sorted vertically by year of publication, with the most recent studies in the bottom and the oldest ones on top. Colored boxes indicate studies included in this review. Out of space considerations, only first author names are given, except in cases of possible ambiguity. CSG: Chinese solar greenhouse; HPS: high-pressure sodium lamps; LED: light-emitting diodes; PV: photovoltaic cells.

Table 4
Validation of greenhouse models. See Section 3.4 for the definitions used here for the seasons, validated variables, and validation metrics. Variables: Ci: indoor CO_2 concentration, DW: harvested dry weight, E: electricity produced, FW: harvested fresh weight, H: heating energy, Hi: indoor humidity, R: radiation, RHi: indoor relative humidity, Tc: cover temperature, Ti: indoor temperature, Tp: plant temperature, Ts: soil temperature, Tw: wall temperature, V: ventilation rate, Wi: indoor wind speed. Validation metrics: d: Wilmott's index of agreement, EF: model efficiency, MAPE: mean absolute percentage error, maxE: maximum error, maxRE: maximum relative error, ME: mean error, MRE: mean relative error, MSE: mean squared error, NSE: Nash-Sutcliffe's coefficient of efficiency, RE: relative error, RMSE: root mean squared error, rRMSE: relative RMSE, SPC: square of the Pearson correlation coefficient, TSSE: total sum of squared error. n/a: information was not available. All studies included plotted graphs of validation results. See Section 3.4 for definitions of commonly used metrics, and the respective publications for definitions of metrics used in only one study, marked with (*).

Reference	Location and season of evaluation	Facility of evaluation (size)	Validated variables	Dataset duration (sampling rate)	Validation metrics	Main validation results
Abbes et al. (2019)	Borj Cedria, Tunisia. Spring	Research (100 m^2)	R, RHi, Ti	19 days (n/a)	MSE, NSE	**R:** NSE = 0.98, MSE = 39 W m^{-2}. **RHi:** MSE = 0.45, NSE = 0.98. **Ti:** MSE = 3.63 °C, NSE = 1
Ahamed et al. (2018a)	Elie, Manitoba, Canada. Spring	Commercial (210 m^2)	H, R, Ts, Tw	3 days (10 min – 1 h)	maxE, ME, MRE, NSE, RMSE, rRMSE,	**H:** rRMSE = 11.5%. **R:** NSE = 0.71, RMSE = 68.34 W m^{-2} **Ts:** NSE = 0.68, RMSE = 1.8 °C
Ahamed et al. (2018b, 2018c)	Saskatoon, Canada. Spring-autumn	n/a (1125 m^2)	H, R	8 months (month)	maxRE, MRE, NSE, RMSE	**H:** MaxRE = 9%, MRE = 4.6%. **R:** NSE = 0.78, RMSE = 112.61 W m^{-2}
Alinejad et al. (2020)	Shiraz, Iran. Full year	Commercial (4081 m^2)	E, H, R, RHi, Ti, V	1 year (monthly)	maxRE	**R:** maxRE <8%, **Ti:** maxRE <3%,
C. Chen et al. (2019)	Beijing, China. Winter	n/a	Ti	2 months (hourly)	d (*)	**Ti:** d = 0.987
J. Chen et al. (2019)	Hangzhou, China. Autumn	n/a (230 m^2)	R	8 h (hourly)	MRE, RMSE	**R:** RMSE = 12.61–21.97 W m^{-2}
De Ridder et al. (2020)	Belgium. Autumn	Research (160 m^2)	Ti	2 × 7 days (20 min)	NSE	**Ti:** NSE > 90%
Esmaeli and Roshandel (2020)	Shenyang, China. Winter	n/a (756 m^2)	Ti	1 day (hourly)	maxE, NSE, RMSE	**Ti:** maxE = 2.8 °C, NSE = 0.95, RMSE = 0.32 °C
Golzar et al. (2018)	Conthey, Switzerland. Winter-autumn	Research (360 m^2)	H, DW	10 months (week-month)	NSE, PBIAS (*), rRMSE	**DW:** NSE = 0.96, PBIAS = 0.18, rRMSE = 23%. **H:** NSE = 0.91, PBIAS = 0.18, rRMSE = 27%
Hemming et al. (2019b)	Bleiswijk, The Netherlands. Summer-autumn	Research (96 m^2)	FW	3 months (weekly)	–	–
Jomaa et al. (2019)	Borj Cedria, Tunisia. Spring	Research (100 m^2)	Hi, Ti	3.5 days (n/a)	–	–
Katzin et al. (2020b)	Bleiswijk, The Netherlands. Autumn-winter	Research (144 m^2)	Ci, H, RHi, Ti	112 days (5 min)	ME, RE, RMSE, rRMSE	**H:** RE = −0.92-11.6%. **RHi:** RMSE = 5.52–8.5%. **Ti:** ME = −0.09-0.05 °C, RMSE = 1.74–2.04 °C
Lammari et al. (2012, 2020)	Avignon, France. Spring-summer	Research (n/a)	Hi, Ti	2 × 7 days (n/a)	–	–
Ma et al. (2019)	Indiana, USA. Autumn	Research (n/a)	R, Ti	7 days (minute)	NSE	**R:** NSE = 0.9, **Ti:** NSE = 0.88
Mohammadi et al. (2020)	Tabriz, Iran. Autumn	Research (15 m^2)	Tc, Ti, Tp, Ts	8 h (minute)	EF (*), MAPE (*), RMSE, SPC, TSSE (*)	**Tc:** SPC = 0.96, RMSE = 2.21 °C. **Ti:** SPC = 0.98, RMSE = 1.64 °C. **Ts:** SPC = 0.98, RMSE = 1.84 °C
Pérez-González et al. (2018)	Guadalajara, Mexico. Autumn, spring	Research (30 m^2)	RHi, Ti	1–3 days (second)	J (*)	J = 5.64–9.4327
Rasheed et al. (2019)	Daegu, South Korea. Winter, autumn.	Research (168 m^2)	Ti	20 days (n/a)	NSE	**Ti:** NSE = 0.79–0.84
Righini et al. (2020)	Klepp, Orre, Norway. Winter, spring, summer	Commercial (5760 m^2), experimental (n/a)	FW, Ti	FW: 3–7 months; Ti: 3×(6–8) days (n/a)	rRMSE, MRE	**FW:** MRE = 0.7–4.3%. **Ti:** rRMSE = 7.1–9.6%
Sethi (2019)	Ludhiana, India. Summer, winter.	Research (100 m^2)	R, Tc, Ti, Tp	7–12 h (hourly)	RMSE	**R:** RMSE = 4.01 W m^{-2}. **Tc:** RMSE = 3.91 °C. **Ti:** RMSE = 4.69 °C. **Tp:** RMSE = 3.7 °C
Su et al. (2018)	Chongming, Shanghai, China. Autumn-spring.	n/a (875 m^2)	Ci, Hi, Ti	5 months (5 min)	RMSE	**Ci:** RMSE = 50 mg m^{-3} **Hi:** RMSE = 1.68 g m^{-3}. **Ti:** RMSE = 2.1 °C
Zhang et al. (2020)	Taian, Shandong, China. Winter, spring.	Prototype (15 m^2)	Tc, Ti, Ts	3 × 15 days (5 min)	ME, RMSE, SPC	**Ti:** SPC = 0.98, RMSE = 1.36–2.01 °C. **Ts:** SPC = 0.66–0.99, RMSE = 0.1–1.93 °C

$$Q_{Latent} = L \cdot W_{Latent} \left(\mathrm{W\ m^{-2}}\right) \tag{10}$$

where L (J kg^{-1}) is the latent heat of evaporation of water, and:

$$W_{Latent} = W_{Trans} + W_{Evap} - W_{Cond} \left(\mathrm{kg\ m^{-2}\ s^{-1}}\right) \tag{11}$$

is the net amount of water transformed to vapor in the system: W_{Trans} is water transpired by the crop, W_{Evap} is water evaporated from the soil, and W_{Cond} is vapor condensed to water on cold surfaces such as the cover or screens. For each of these components W, the associated energy flow is $L \cdot W$. Not every change in the water vapor balance is associated with latent heat exchanges: for example, loss of water vapor through ventilation W_{Vent} (Eq. 6) is not in itself associated with a change in the energy balance.

2.4.6. Transpiration

A wide range of approaches can be used for modelling crop transpiration, as outlined in detail by Katsoulas and Stanghellini (2019). These approaches range from an empirically fitted function where transpiration depends only on solar radiation, through aerodynamic models that include the influence of wind, to detailed models that include the energy balance of the crop and the response of stomata to environmental attributes including total radiation intercepted by the crop, vapor pressure deficit (VPD), air temperature, and CO_2 concentration.

One of the simplest ways to model transpiration is to treat it as a linear function of radiation:

$$W_{Trans} = A_0 I_{Sun} + B_0 \ \left(\text{kg m}^{-2}\ \text{s}^{-1}\right) \quad (12)$$

Where I_{Sun} (W m^{-2}) is radiation from the sun, and A_0 (kg J^{-1}) and B_0 (kg m^{-2} s^{-1}) are fitted parameters that may depend on the crop, the crop stage, or the growing season.

Another common way to model transpiration is the Penman-Monteith formula (Monteith, 1965), which describes the latent heat of evaporation from a leaf (shown here using the notation of Katsoulas and Stanghellini (2019)):

$$Q_{Trans,leaf} = \frac{\Delta R_n + \rho C_p D_i g_a}{\Delta + \gamma(1 + g_a/g_c)} \ \left(\text{W m}^{-2}\ \{\text{leaf}\}\right) \quad (13)$$

where Δ (kPa K^{-1}) is the slope of relationship between saturation vapor pressure and temperature, R_n (W m^{-2} {leaf}) is the net radiation intercepted by the crop, ρ (kg m^{-3}) is the density of air, C_p (J kg^{-1} K^{-1}) is the specific heat of air, D_i (kPa) is the vapor pressure deficit of the air, g_a (m s^{-1}) is aerodynamic conductance, γ (kPa K^{-1}) is the psychrometric constant, and g_c (m s^{-1}) is stomatal conductance. Transpiration $W_{Trans,leaf}$ in kg m^{-2} s^{-1} is then calculated by dividing $Q_{Trans,leaf}$ by the specific heat of water evaporation, see Eq. 10.

Stanghellini (1987) modified the Penman-Monteith formula for the case of greenhouse crops. First, a factor for crop leaf area index (LAI, m^2 {leaf} m^{-2} {floor}), which expresses the leaf area of the crop per area of greenhouse floor, was used in this case to convert leaf transpiration to crop transpiration:

$$Q_{Trans} = \frac{\Delta R_n + 2 \cdot LAI \cdot \rho C_p D_i g_a}{\Delta + \gamma(1 + g_a/g_c)} \left(\text{W m}^{-2}\ \{\text{floor}\}\right) \quad (14)$$

Furthermore, calculation of the aerodynamic conductance g_a was modified to describe a greenhosue environment. Lastly, stomatal conductance g_c was calculated following the approach of Jarvis (1976), where stomatal conductance depends on environmental factors such as radiation, vapor pressure deficit, temperature, and CO_2 concentration:

$$g_c = g_M f_1(R_n) f_2(D_i) f_3(T_i) f_4(CO_2) \ \left(\text{m s}^{-1}\right) \quad (15)$$

The notation here follows, again, Katsoulas and Stanghellini (2019) (see Eq. 13). Here, g_M (m s^{-1}) is the maximal stomatal conductance, and f_1, f_2, f_3, f_4 are unitless functions with values between 0 and 1 that represent the influence of, respectively, radiation, vapor pressure deficit, temperature, and CO_2 concentration on stomatal conductance. Villarreal-Guerrero et al. (2012) discussed the differences between the Penman-Monteith and the Stanghellini transpiration models, and compared their performances against measured data.

In the equations above, T_i may refer to either the air or the crop temperature, and D_i may refer to either the vapor pressure difference of the air or the vapor pressure difference between the saturated vapor pressure at the temperature of the crop and the saturated vapor pressure of the air. If crop temperature is used in the calculation of transpiration, then naturally this attribute must also be included in the greenhouse model. Similarly, if LAI is included in the calculation of transpiration, some estimate, assumption, or model describing LAI must also be included.

Another approach for modelling transpiration is based on the assumptions that the indoor water vapor concentration is in steady state, and that all vapor flows besides ventilation are negligible. Considering Eq. 1, this leads to $W_{Trans} = W_{Vent}$, which allows to estimate transpiration based on ventilation rate and indoor and outdoor vapor concentrations (Eq. 6).

2.4.7. Condensation

Condensation occurs when humid air is in contact with a surface that is colder than the dew point of the air. Equivalently, this means that the saturation vapor pressure at the temperature of the surface is higher than the vapor pressure of the air. Condensation typically occurs on the indoor side of the greenhouse cover or on screens, but may also happen on the crop itself, the floor or soil. An equation to describe condensation is:

$$W_{Cond} = max\left\{0, g\left(V_{Air} - V_{Surface}\right)\right\} \ \left(\text{kg m}^{-2}\ \text{s}^{-1}\right) \quad (16)$$

where V_{Air} (kg m^{-3}) is the vapor concentration of the air, $V_{Surface}$ (kg m^{-3}) is the saturation vapor concentration at the temperature of the surface, and g (m^3 m^{-2} s^{-1}) is an exchange coefficient. This coefficient g may be related to the heat exchange coefficient h in Eq. 8, for instance it may be proportional to it.

2.4.8. Crop photosynthesis

Leaf and canopy photosynthesis modelling is a broad and long-standing discipline with an extensive range of approaches (Hikosaka et al., 2016). Earlier reviews described some of the crop modelling approaches used in horticulture (Gary et al., 1998) and in greenhouses in particular (Marcelis et al., 1998).

As with transpiration, photosynthesis models range from very simple models where only light is taken into account, to complex models including the influence of temperature, CO_2 concentration, and crop processes such as assimilate demands of the various organs. A yield model may also be included, predicting how much produce can be sold by the greenhouse, and when. Again, the level of detail varies considerably between such models (Kuijpers et al., 2019). The type of crop may influence the level of detail: leafy crops such as lettuce typically require less detail than fruiting crops such as tomato or cucumber.

As with transpiration, a description of the leaf area index (LAI) and its development through time may also be included in the crop model. In any case, LAI is typically an important component of the photosynthesis model. This means that even if a simple photosynthesis model is used, some assumption or estimate regarding LAI is needed.

2.5. Time scales in greenhouse climate models

The dynamics of the greenhouse climate are influenced by processes which may be classified as "fast" and "slow" (e.g., Tap et al., 1993; Van Henten, 1994; Van Straten et al., 2010). The slow variables are typically related to crop processes, which evolve in the order of days, weeks, and months. The fast variables are related to climate variables, which can evolve in the order of seconds, minutes, and hours. These widely different time scales often cause inaccurate or inefficient results during numerical integration (i.e., during greenhouse simulation), especially in studies related to optimal control (Tap et al., 1993; Van Straten et al., 2010).

Thus, a common approach is to separate the state variables of a greenhouse into fast and slow time scales, and compute these two time scales separately. The fast variables may be assumed to "achieve a steady-state infinitely fast" (Van Henten and Bontsema, 2009). In effect, this results in setting the differential equations governing the fast states to be constantly zero. This decomposition into fast and slow dynamics helps circumvent many of the numerical issues during integration, and results in more efficient computation. Furthermore, this decomposition helps analyze and understand the behavior of the greenhouse system along the different time scales (Van Henten and Bontsema, 2009).

Nevertheless, a distinction should be made between how a model describes the dynamics of a greenhouse system, and how this description is used when the system is solved or integrated in practice. For example, the Van Henten model (Eq. 2) may be used in some cases without any time scale decomposition (Van Henten, 2003), while in other cases such a decomposition proves useful (Van Henten and Bontsema, 2009). Similarly, during the development of the De Zwart model (Eq. 4), a choice was made to compute some variables using "a static equation", since "the dynamics [...] [are] of a small time base" (De Zwart, 1996). In other words, it is assumed that some of the climate dynamics are faster than others, namely, those related to the air above the screen and to other objects with a small heat capacity. Again, the assumption is that these faster states achieve a steady state infinitely fast, which results in an equation with a left-hand side equal zero. This includes for example the temperature of the screen and the temperature of the air above the screen, represented by the second and third lines of Eq. 4. However, since the dynamics of these variables are still described, one could choose to use the De Zwart model and reject this "static" assumption, if the need arises.

Alternatively, some models choose to completely avoid describing the slow states. For example, Van Beveren et al. (2015a, 2015b) assumed that the crop, and specifically the LAI, remained constant throughout the simulated season. Conversely, Vanthoor et al. (2011c) combined a crop and greenhouse model, where despite these two models operating in different time scales and both containing numerous state variables, all states were directly and simultaneously calculated using differential equations.

3. Review of recent greenhouse modelling studies: Methodology

In order to examine the current state of greenhouse modelling, a literature search was performed on Clarivate's Web of Science (www.webofscience.com). Since the term "greenhouse" is widely used in non-horticultural contexts, a search for simply "greenhouse model" or "greenhouse AND model" was unfeasible, yielding over 8000 results, most of them irrelevant. Instead, the search term chosen was: ("greenhouse model*" OR "greenhouse simulation*" OR (greenhouse* AND ("yield model*" OR "thermal model*" OR "heating model*" OR "yield simulation*" OR "thermal simulation*" OR "heating simulation*" OR "optimal control")) NOT ("greenhouse gas*" OR "greenhouse emission*" OR "greenhouse effect*")). The search was performed on October 6, 2020, for articles in the Web of Science Core Collection, published in 2018–2020, whose topic (title, abstract, keywords, and Keywords Plus) matched the search term. This three-year period was chosen as representative of the current state of the art in greenhouse modelling. The search yielded 80 results. Of these, 48 articles were excluded: 15 that described models of components of the greenhouse system; 12 that discussed unrelated topics; 7 that discussed greenhouse dryers; 5 that described real world, scaled down models of greenhouses; 5 review studies; 3 descriptive models; and 1 CFD model. Thus, 32 articles published in 2018–2020 were considered in this study.

3.1. Overview of greenhouse modelling studies

The studies in the 32 articles were analyzed as follows: first, the study objectives were divided into 5 categories (see Section 2.2), including exploratory modelling, model-based control, model-assisted design, and systems analysis. Another category was included for studies focusing on model calibration methods. Next, a more specific purpose of each study was summarized according to the authors' descriptions. The greenhouse type, crop, and equipment modelled were described based on the authors' descriptions or, when those weren't provided, on the conditions used during model validation. For greenhouse type, we defined a Venlo greenhouse as an even-span greenhouse with glass cover and walls. A Chinese solar greenhouse (CSG) was defined as a low greenhouse with a northern wall which provides diurnal heat storage. A southern cover arching from the northern wall to the southern edge of the CSG is equipped with a thermal blanket or screen that maintains heat in the greenhouse overnight.

Lastly, studies were categorized according to the development status of the models used: **new:** newly presented models (possibly combining several previous works, but not explicitly derived from a single previous model); **reuse:** exact copies of a previous model; **parametrization:** models combining a single previous model with a new set of parameters; **extension:** models explicitly using a single previous model and adding components to it; and **translation:** previously published models presented using new code or a new software platform.

3.2. Composition of process-based greenhouse climate models

In order to get a better understanding of the differences between models that are currently used, the models were analyzed and compared with regards to how they handle the various greenhouse model components. These components included:

- **Energy balance:** heating from the sun, the heating system, and supplemental lighting; number of objects considered in thermal radiation exchanges; number of objects considered in convective and conductive exchanges; ventilation; latent heat.
- **Water vapor balance:** transpiration (variables influencing it and model used), evaporation and condensation (number of objects considered).
- **CO_2 balance:** photosynthesis and yield (factors influencing them, and model used).
- **Leaf area index** (LAI).

For each component, we noted whether the model introduced a new method for calculating the component, or if a previous study was used. We noted which previous work was used for a specific component, if this was noted. If a component based on previous works was modified (simplified or extended), this was also noted.

3.3. Inheritance of process-based greenhouse climate models

In order to explain the differences between current models, the models were further investigated by examining which previous models they were based on, and how they had modified or combined them. This was done based on the authors' descriptions, together with our own comparison of the published model with previously published models. The models included in this study were compared against their reported "parent" to see whether components were added or modified, and how. The parent models were also checked to see whether they themselves were based on common earlier works. We also noted whether some of the same authors were involved in the publications describing the parent and the daughter models. For this purpose, promotors and supervisors were considered as coauthors of PhD dissertations.

3.4. Validation of greenhouse models

For all models that presented a validation simulation, the following attributes were collected:

- Location and season where measured data was collected. Here, meteorological seasons of northern latitudes were used: **Winter:** December–February; **Spring:** March–May; **Summer:** June–August; **Autumn:** September–November (all studies considered were performed in the northern hemisphere).
- Type and size of the facility where data was collected, if it was provided: research greenhouse, commercial greenhouse, or scaled-down prototype.
- Validated variables, i.e., variables that were predicted by the model and compared against measured data.
- Duration of time in which data was collected, and sampling rate of data points.
- Metrics used for validation.
- Main validation results, rounded to 2 decimal points.

Metrics used for validation varied considerably between studies, as well as the terms used to describe these metrics. The definitions below, following Legates and McCabe (1999), were used when noting the validation metrics. Here, we denote by y_i the measured values, f_i the predicted values, $\bar{y}$ the mean of the measured values, $\bar{f}$ the mean of the predicted values, $\sum$ summation over i, and max the maximum over i, where $i = 1, \ldots, n$ is an index ranging over measurements and corresponding predictions.

- Mean error: $ME = \frac{1}{n}\sum(f_i - y_i)$
- Maximum error: $maxE = \max\{f_i - y_i\}$
- Mean relative error: $MRE = \frac{1}{\bar{y}\cdot n}\sum(f_i - y_i)$
- Maximum relative error: $maxRE = max\left\{\frac{f_i - y_i}{\bar{y}}\right\}$
- Mean squared error: $MSE = \frac{1}{n}\sum(f_i - y_i)^2$
- Root mean squared error: $RMSE = \sqrt{\frac{1}{n}\sum(f_i - y_i)^2}$
- Relative root mean squared error: $rRMSE = \frac{1}{\bar{y}}\sqrt{\frac{1}{n}\sum(f_i - y_i)^2}$
- Square of the Pearson correlation coefficient: $SPC = \frac{\left(\sum(y_i - \bar{y})(f_i - \bar{f})\right)^2}{\sum(y_i - \bar{y})^2\sum(f_i - \bar{f})^2}$
- Nash-Sutcliffe's coefficient of efficiency: $NSE = 1 - \frac{\sum(y_i - f_i)^2}{\sum(y_i - \bar{y})^2}$

Some ambiguity was found with respect to the terms "coefficient of determination", "correlation coefficient", "explained variation", "explained variability", "r^2", and "R^2". These terms were often used to mean either the SPC or the NSE as defined above. In some cases, no reference or equation was given, which made it difficult to determine which of the metrics was actually used. In these cases, we assumed that the NSE was used. Whenever equations were given for the metrics used, they were reported according to the definitions above. For other metrics, if no definition was given, the term given by the authors was used.

Some words are in order regarding terminology. It has been noted that the term "validation" may be interpreted as aiming to provide a clear yes or no answer regarding the adequacy of a model: the model is either valid or it is not. For this reason, some have suggested to avoid the term "validation" and use "evaluation" instead (Wallach et al., 2019a). Nevertheless, the two terms are often used interchangeably. In this study, we use the term "validation" in a narrow sense, as the comparison of model predictions against measured data. The term "evaluation" is understood in a broader sense, which includes validation but may also include other components, such as the process of data collection.

3.5. Studies used in each analysis

In the investigations of model composition and inheritance, models based on software platforms such as TRNSYS, EnergyPlus or COMSOL (see Section 2.1) were excluded from the analysis, since their descriptions were typically insufficient for users unfamiliar with these programs to understand the inner workings of the model. In the analysis of model inheritance, only complete greenhouse models were considered as eligible parent models. For the sake of clarity, the inclusion or combination of model components, such as a separate transpiration or convection model was not described in the inheritance chart. Naturally, for the analysis of model validation, only studies presenting any kind of validation were considered.

For some studies included in this review, the details of the model described were given in a previous publication. In these cases, we used information from the previous publication to analyze the model composition, inheritance and validation. This was done for Ahamed et al. (2018c) by also considering Ahamed et al. (2018b); for Lammari et al. (2020) by including Lammari et al. (2012); and for Esmaeli and Roshandel (2020) with Esmaeli and Roshandel (2017).

4. Results: Current state of the art in greenhouse modelling

4.1. Overview of greenhouse climate modelling studies

The studies considered in this review vary in their purposes, types of greenhouse considered, and equipment included in the greenhouse. The majority of the studies considered (11 of 32) focus on greenhouse climate control (Fig. 4). Studies focused on design are also common (8 of 32), followed by systems analysis (6), exploratory modelling (4), and model calibration (3), although the distinctions between these categories was not always clear (Table 2).

In studies focused on control, various methods for climate control were described and evaluated, such as adaptive control, fuzzy logic, and more (Table 2). Model-based design was used for designing a complete greenhouse system or specific components such as placement of PV cells. Systems analysis was used to analyze the greenhouse energy use, environmental impact, or the model itself. Exploratory modelling was used to test scenarios with different designs, control strategies, and equipment. Model calibration studies proposed new methods for calibration or identification, such as particle swarm optimization and deep networks.

More than a third of the studies (11 out of 32) presented new models, and the same number of studies was devoted to extensions of previous models (Fig. 4). Reuse of existing models was less common (9 out of 32 cases). One study presented a translation of an existing model to a new software platform. New models were created to describe new types of greenhouses (e.g. CSGs, asymmetric overlap roof), to implement models on specific platforms (e.g. TRNSYS), to include new technologies (lamps, heat harvesting), or to incorporate detailed model components (cover absorbance, thermal screens) (Table 2). Notably, 6 studies defined the development of the model itself as a study purpose, and 8 studies defined the use of a certain methodology as a purpose.

In the majority of cases (11 of 32), the crop in the modelled greenhouse was tomato (Fig. 4). This could be expected, as tomato is by far the most widely produced and exported vegetable in the world, excluding potato and melons (Rabobank, 2018). The low representation (3) of ornamental crops is surprising, as they make up at least half of the world's greenhouse production (Stanghellini et al., 2019). Remarkably, several models (5) were designed or evaluated under the assumption that the greenhouse does not house any crop.

The types of modelled greenhouses could broadly be classified into three: Venlo glasshouses, Chinese solar greenhouses, and polyethylene greenhouses (Fig. 4). CSGs varied in the type of covering material used, and polyethylene greenhouses varied in shape (Table 2). The modelled greenhouses also varied considerably in the equipment they included, with heating the most common equipment included (19 of 32 studies), followed by lighting (15 studies in total), CO_2 injection (12), fogging (7), and thermal screens (7) (Fig. 4).

4.2. Composition of process-based greenhouse climate models

As described in Section 2.4, greenhouse climate models describe a large number of processes, and a vast range of approaches is available for each process. Among the models analyzed in the current studies, these differed considerably in how they incorporated the various greenhouse system components (Table 3). At the same time, there is considerable overlap between the models analyzed, which could possibly result in redundancy. A considerable amount of model development (14 of 24 models analyzed) consisted of putting together previously published components; less than half of the studies (10 of 24) described newly developed model components. The solar heat load was typically given as a model input or set as a fixed proportion of an input. Heating was typically given as an input or calculated based on other energy fluxes. When lighting was included, the resulting heating load was often assumed to be proportional to the lamp power input, no matter the lamp type (6 out of 9 cases). In 2 cases describing LEDs, it was assumed that light does not contribute any heat to the greenhouse. The number of objects included in thermal radiation (FIR) exchanges varied from 0 to 11, and the number of objects included in convective exchanges varied from 2 to 18. Ventilation was neglected (2 out of 24 cases), assumed constant (5 cases), given as an input (8 cases), or calculated based on various variables (9 cases). Latent heat was not included in 5 out of 24 models, and in 3 only the influence of fogging was included. LAI was excluded (9 of 24 cases) or assumed constant (8 cases) by a majority of the models. Approaches to modelling transpiration varied considerably, as previously noted by Katsoulas and Stanghellini (2019). Relatively few models considered photosynthesis (9 of 24) and yield (8 of 24), and approaches varied between those that did.

Regarding the time scales included in the models, all models that did not include a yield component (16 of 24) considered only the fast dynamics of the greenhouse climate and neglected the slow dynamics of the crop. In 6 out of the remaining 8 models, both the fast dynamics of the greenhouse climate as well as the slow dynamics of crop development were included. In the model of Seginer et al. (2020b), the crop was assumed to be mature, and therefore “steady”, with yield directly proportional to net photosynthesis. Similarly, Katzin et al. (2020b) assumed that the crop was mature, and therefore LAI and crop development status were constant.

4.3. Inheritance of process-based greenhouse climate models

Some of the differences and similarities between models can be explained by the model inheritance chart (Fig. 5). For example, it can be seen that the models of Katzin et al. (2020b) and of Righini et al. (2020) were both extensions of Vanthoor et al. (2011b) and that the models described in Pérez-González et al. (2018) and in Lammari et al. (2020) both originated with Boulard et al. (1996). The models used by Mohamed and Hameed (2018), Gharghory (2020), and Subin et al. (2020) all originated with the model of Albright et al. (2001). It can also be seen that several early models (Albright et al., 2001; Boulard et al., 1996; De Zwart, 1996; Vadiee and Martin, 2013; Van Henten, 1994; Van Ooteghem, 2007) are still used as a basis for many recent studies. These models are based on even earlier models (Bot, 1983; Boulard and Baille, 1987; Garzoli, 1985). Some models combine several earlier models (e.g., Lammari et al., 2012 combines Albright et al., 1985; Boulard et al., 1996; Draoui, 1994), while others are reportedly based only on a single previous model (e.g., Tchamitchian, 1992 is based on Udink ten Cate, 1983, and Taki et al., 2016 is based on Van Ooteghem, 2007). The model of Tiwari, 2003 was used to convert the model of Ahamed et al., 2018b to a CSG (Ahamed et al., 2018a). At the same time, for several recent studies (Ahamed et al., 2018a; C. Chen et al., 2019; De Ridder et al., 2020; Sethi, 2019) we were not able to identify whether they were based on previous greenhouse models, and if so, on which.

In many cases where a model was reused or extended, authors of the parent model were also involved in the new study. In 7 out of 11 cases of model extension, the original and extended model shared coauthors. The same was true for 4 out of 9 cases of model reuse. Cases of model reuse or extension by authors unrelated to the original publication are limited to quite simple models, as can be seen by their decomposition in Table 3: Xu et al. (2018a) reused the model of Van Henten (2003); Mohamed and Hameed (2018) reused the model of Albright et al. (2001); Gharghory (2020) and Subin et al. (2020) reused the model of Pasgianos et al. (2003); and Jomaa et al. (2019) reused the model of Blasco et al. (2007), while using parameters from a previous study. Model extension without shared coauthors is also reserved for relatively simple models, e.g. the extensions by Xu et al. (2018b, 2019) to Van Henten (2003), the extension by Su et al. (2018) to Tap (2000), and the extension of Pérez-González et al. (2018) to Hasni et al. (2011).

4.4. Validation of greenhouse climate models

Models differed in the techniques used for validation in all aspects considered: the facilities used for data collection, the validated variables, the dataset length and sampling rate, and in validation metrics (Table 4). The size of the facility used varied from a 15 m^2 prototype to a 5760 m^2 commercial greenhouse. The validated variables typically included the indoor temperature, but other variables were also considered, such as indoor humidity, radiation inside the greenhouse, and heating energy used. Dataset length varied from less than a day to a full year, and the sampling rate of measurements varied from one second to one month. Overall, the sizes of datasets used for model validation were rather small, with datasets representing the major part of a year (8–12 months) only consisting of weekly or monthly measurements. In terms of validation metrics, no common standard was found. All studies included graphs comparing measured and simulated values. Some studies added no information beyond the presented graphs, while others used multiple metrics to analyze the model predictions. RMSE was the most common metric for validation (used in 9 of the 22 studies), followed by NSE (8 studies). Other metrics were also used, with some used only by a single study. Because of this wide range of evaluation methods, differing in timespan, sampling rate, validated variables and validation metrics, it is practically impossible to compare model performance based solely on validation results.

5. Discussion

5.1. What is the source of variation between greenhouse climate models?

The vast range of crops, structures, equipment and climates that characterizes greenhouse horticulture does not seem sufficient to explain the variation between greenhouse models. The majority of studies reviewed considered a tomato crop, while many others assumed an undefined generic crop or no crop at all (Fig. 4). Adding new equipment to an existing greenhouse model is sometimes a motivation for model extension (Fig. 5), but that in itself does not seem to justify the development of entirely new models. Regarding structure type, most studies were concerned with Venlo type greenhouses (Fig. 4), although a considerable number of studies focused on CSGs, and several were devoted to transforming an existing model to a CSG (Fig. 5). This seems to indicate a growing interest in the modelling of CSGs. It remains to be seen whether this trend will continue. Arguably, this will depend on developments in the global greenhouse sector, and the prevalence of CSGs compared to other types of greenhouses.

Modelling objective provides a better, although partial, explanation to model variation: the most complex models found in this study, with 16 or more objects included in convective exchanges, were all devoted to exploratory modelling (Table 3). At the other end of the complexity scale, studies focused on calibration and control tended to use simple models, with few objects included in the convective and FIR exchanges. Out of 11 models that were found to have 3 or less convective objects, 7 dealt with control and 2 with calibration (Table 3). Studies on calibration and control tended to focus less on accurate predictions, and often lacked validation (Table 4). The approach in these studies was also more generic compared to exploratory studies, often providing little detail on the type of structure or crop, and even neglecting the crop completely (Table 2).

Thus it may be argued that models devoted to exploratory modelling require a high level of complexity while models devoted to control and calibration require a low level of complexity. If this were the case, it would explain some of the variation in greenhouse modelling. However, exceptions do exist, with the relatively simple model of Ahamed et al. (2018a), with only 5 convective objects, devoted to exploratory modelling, while the relatively complex model of Abbes et al. (2019), with 8 convective objects, dedicated to control. Of course, one may also argue that the number of convective objects is not the only way to quantify model complexity, a concept which remains open for interpretation.

In any case, the distinction between detailed and complex "prediction-focused" models and simpler "control-focused" models goes back at least to the 1980's, when Bot (1983) and Udink ten Cate (1983) developed in parallel models that represented these two objectives. Tap (2000) reported that in 1986, Vennegoor op Nijhuis compared these two models as part of an MSc thesis and found them to be similar in terms of predictions, with the model of Udink ten Cate being considerably faster in terms of computation time. Indeed, a preference for simpler models in control applications due to computational issues remains relevant to this day: see for example the discussion in Van Henten and Bontsema (2009), or the several technical steps required in Xu et al. (2018a) to obtain an accurate and fast solution to an optimal control problem.

At the same time, it seems reasonable that models designed for predicting scenarios would include many processes. First of all, because new insights regarding particular system components and processes can only be uncovered if those components and processes are included in the model. Second, there seems to be an agreement between model developers and users that model structure, i.e., the assumptions and relationships underlying the model, are important factors when assessing the reliability of a model for exploratory simulations (Eker et al., 2018). This view could explain why models developed for prediction tend to incorporate many process-based relations based on physical and biological principles, rather than summarize phenomena with simpler functions: the inclusion of phenomena which are understandable and trusted by a potential user (or the model developer) promotes trust in the model and its predictions.

Another factor that could contribute to model variation, and may be related to the modelling objective, is the issue of time scales. As mentioned in Section 2.5, including different time scales in a model can result in computational difficulties, especially in studies devoted to optimal control. Thus, control-focused studies may prefer to neglect the slow processes of crop development and focus only on the fast climate dynamics of the greenhouse. Alternatively, design-focused studies may neglect some of the fast climate responses which do not have a strong influence on the performance of a greenhouse over a full year.

Nevertheless, the majority of models found in this survey, including models from all categories of objectives, did not include the slow crop dynamics (Table 3). Models that did include the slow time scales were used in studies focused on exploratory modelling, greenhouse design, and climate control. The four design studies analyzed all included relatively few objects in the heat exchange balances, which indicates that indeed, these studies tend to simplify the fast climate dynamics. At the same time, one design study included the slow crop dynamics, showing that opinions vary regarding which time scales are the most appropriate for each type of study. We see then that the issue of time scales, and the way those are treated in order to serve the modelling objective, seems to contribute to some of the variation we see among models.

In any case, although modelling objective seems to give the best explanation for the wide range in model complexity, it should be stressed that it is often difficult to accurately extract a given model's objective based on the authors' descriptions. In particular, the distinctions between exploratory modelling, design, and system analysis are not always clear-cut (Table 2). Furthermore, in some cases, the impression could arise that models were developed solely for the purpose of developing them. In other cases, the main objective seems to be the demonstration of a certain methodology, and the accurate representation or application for greenhouses seems secondary. The objectives assigned to the models throughout this study (Fig. 4, Table 2, Table 3) should be viewed with this observation in mind.

5.2. How complex should process-based greenhouse climate models be?

Seeing the vast range in model complexity, a question that arises is how complex greenhouse models should really be. This question is extensively debated in the context of crop modelling (Antle et al., 2014; Hammer et al., 2019; Keating, 2020; Monteith, 1996; Passioura, 1973, 1996; Sinclair and Seligman, 2000). Monteith (1996) advocated finding a "balance" between simplicity and complexity. He stressed that complex models are more difficult to understand and that it is often easier to derive insights from simpler models, even if those may provide less accurate outputs.

Unfortunately, besides this general advice and the view that simple models are often preferable, it is hard to find very practical advice regarding model complexity. Passioura (1996) maintained that crop models should be "as simple as possible" and should have "a small appetite for data". Keating (2020) reiterated a statement attributed to Albert Einstein that "the model should be as simple as possible in the context of intended application, but no simpler". In the context of greenhouse modelling, Vanthoor (2011) proposed that developing simple models is often easier said than done: "According to Johan Cruijff simple soccer is the most difficult to play, and unfortunately, this also applies to simple modelling". Efforts to methodologically address the question of model selection, as has been done for example by Crout et al. (2009) in the context of environmental modelling, are rare in crop modelling, and even more so in greenhouse modelling.

At the same time, there is quite some evidence to attest to the power of simple models: Stockle (1992) showed that a photosynthesis model can be considerably simplified, and thus be made easier to use and understand, without meaningfully increasing its prediction error. Soltani and Sinclair (2015) demonstrated that simple crop models sometimes provide more accurate predictions than complex ones. In the context of greenhouse crops, the case of the TOMGRO tomato crop model is remarkable, where the number of state variables was reduced from 574 to 5, while still achieving good predictions (Jones et al., 1999). At the same time, the success of such model reduction endeavors strongly depends on the purpose of the modelling study and the sensitivity of the model and its sub-processes towards this particular purpose.

Considering the large number of processes and objects that may be present in a model (Table 1, Table 3), and the general preference for simpler models, a natural question to ask is which of them should be included for any particular modelling purpose. Naturally, a modelling study that examines the influence of a particular process or object (e.g., reduced crop transpiration, or the use of a thermal screen), must include the process or object in question in the model. Besides that, one way to test which other processes should be included could be by starting out with a complex model, and testing each process individually for its influence on the intended objective. Processes that are found to have little influence on the objective could then be consecutively omitted. However, it should be noted that the influence of each process depends not only on the modelling objective, but also on the specific settings such as location of the greenhouse, type of structure, type of crop and crop stage, and more. These factors will also influence which processes are dominant and which are negligible for a given modelling objective.

Another, and hopefully less cumbersome approach, would be to compare existing simple and complex models and test how they serve a given modelling objective. Unfortunately, it is very difficult to compare the performance of greenhouse models (Section 4.4). Constructing a framework where greenhouse climate models could be compared and evaluated using a common dataset of measurements would help elucidate how model complexity influences model performance. A common framework for decomposing and comparing tomato crop models has been presented by Kuijpers et al. (2019). It could be valuable, although considerably more complex, to construct such a framework for greenhouse climate models.

5.3. Why are so many different models being used and developed?

As mentioned in Section 1, the abundance of greenhouse models is not new. More than 30 years ago, Van Bavel et al. (1985) called to focus efforts on the improvement of existing greenhouse models, rather than "the writing of entirely new programs and the construction of new models". Not much later, Lacroix and Zanghi (1990) urged that "rather than build new models, it should usually be sufficient to take up existing models, adapt them to specific needs and improve them further" (translated). These calls seem to have remained unheeded, with many models still being developed, several of which serving similar purposes (Table 2).

A possible explanation for the abundance of greenhouse climate models is the large variety in types of greenhouses. Indeed, greenhouses are used in widely different climatic environments, with various types of flooring and soil, numerous shapes and designs, diverse covering materials, and various cropping techniques. Nevertheless, this wide variation in itself does not seem to justify the proliferation in models. For example, the abundance of models representing Dutch greenhouses and climate conditions seems incongruent with the relative homogeneity of this country's climate and greenhouse sector. Furthermore, some of the varying attributes listed above could be treated by a single model by modifying its parameters. This was done for instance by Vanthoor et al. (2011b), who used a single model with different parametrization to represent an arch shaped multi-tunnel polyethylene greenhouse in Italy, a Venlo type greenhouse in the Netherlands, a Venlo type greenhouse in Texas, and an arch shaped single-tunnel polycarbonate greenhouse in Arizona, all with satisfying results.

A more plausible reason for the current model abundance is that some models seem to be developed simply for the sake of developing a model (Table 2). Granted, a study may have several purposes, some stated more explicitly than others, and the definition of a study's purpose as described in Table 2 is based on subjective interpretation. Nevertheless, clear motivation behind a particular model's development is often missing, and it seems that model development is in itself considered a worthwhile research objective. This issue has been previously identified in the field of crop modelling (Sinclair and Seligman, 2000). Moreover, the lack of an explicit statement of modelling objectives makes it difficult to judge whether a given model serves its intended purposes, or if it is suitable for use by others to serve their own goals.

Another possible reason for the creation of new models rather than building on existing ones is an issue raised by Holzworth et al. (2015) in the context of agricultural modelling: "maintenance of documentation and software/code has not been considered a core research outcome [...] This results in software that is maintained in an ad-hoc fashion to the point where often the best way forward in improving the software base is to start from scratch". In this case, Holzworth et al. (2015) seem to assume that model code is available but poorly maintained. In greenhouse modelling, matters are arguably worse, since it is rarely the case that code is made available at all, so that indeed the only way forward is to start from scratch.

Reuse of existing models is also limited due to poor reporting. When code is not available, potential users are driven to reproduce models based on equations printed in published papers. This method is vulnerable to mistakes such as misprints and omission of details, made worse when old models are reprinted using new notation (e.g., new variable and parameter names). Another issue is imprecise referencing, for example when whole books (containing multiple models) are provided as a reference to a model being used, or when several references are given without an explanation on how they were used or combined.

The suspicion that new models are being developed simply because older models are not available is strengthened by the model inheritance chart (Fig. 5): when reusing or extending existing models, researchers predominantly choose their own models as a basis for further work. Cases where the work of others has been reused or extended are typically restricted to simple models, where reproduction is arguably easier. This observation is in line with that of Holzworth et al. (2015) who remarked: "[the] model fit-for-purpose question is usually overlooked in favor of adopting an off-the-shelf model, likely one with which the researchers have some experience, regardless of its possible complexity misfit". A similar tendency has also been found in the field of hydrological modelling (Addor and Melsen, 2019).

5.4. Model validation

5.4.1. To what extent are greenhouse models valid?

An essential component of model development is the validation of model predictions against measured data. In greenhouse modelling, evaluations vary considerably in their approaches. Details on if and how data was used for model development (e.g., for parameters calibration) are often missing. In this review, the size of the measured dataset varied considerably in the duration and sampling rate of the measured timespan, and in the majority of cases (13 of 22) data was collected in relatively small research facilities (Table 4). Regarding sampling rate, it may be expected that processes such as crop yield or energy use may be aggregated over a longer timespan than fast processes such as the indoor climate. However, in general there was no agreement between the relevant time scale of a variable and the sampling rate used for its validation (Table 4). Naturally, model developers can only work with the data they have. However, reflections are scarce on whether the data used for evaluation is truly representative of the system being modelled (Wallach et al., 2019a).

Considerable differences also exist in the metrics used in model validation (Table 4). This abundance of metrics may be seen as a positive development, since validation studies of greenhouse models in the 1980's and 1990's often provided only graphs of measured vs simulated values and some qualitative remarks about the model predictions such as "good", "fair", or "reasonable". As noted earlier (Section 3.4), the terms currently used for validation metrics are inconsistent, with several different names given to the same evaluation metric, and worse – the same names used for two different metrics, namely, terms such as "coefficient of determination", "correlation coefficient", and "R^2" used for both the SPC and the NSE. This confusion seems to stem from the fact that when a model is derived using a linear least squares regression, the SPC and NSE are equivalent. However, process-based greenhouse models are rarely based on linear regression. In fact, it is unclear why SPC is used at all in this context: authors who use it state (sometimes implicitly) that an SPC value close to 1 automatically represents good model predictions. However, this is a misconception, as a high SPC will only indicate that there is a linear relationship between measured and predicted values. For instance, measured values of $y = 1,2,3$ and predicted values of $f = 500,0,-500$ will yield SPC $= 1$, despite the model being completely off in both the trend and the order of magnitude. These attributes led Bellocchi et al. (2010) to conclude that the use of the SPC to evaluate model performance is "flawed". Kobayashi and Salam (2000) give an example of how the SPC can be misleading, as it obscures important information for assessing model performance.

Various scientific disciplines hold long ongoing debates regarding the most effective methods for model evaluation and validation (Bennett et al., 2013; Eker et al., 2018; Legates and McCabe, 1999; Oreskes et al., 1994), including the crop modelling community (Bellocchi et al., 2010; Cao et al., 2012; Kobayashi and Salam, 2000; Wallach et al., 2019a; Yang et al., 2014). It seems that in greenhouse modelling this debate has so far been absent, resulting in model developers each coming up with their own methods for evaluation, and some simply not validating or evaluating their model at all. The diversity in model validation metrics makes it difficult to compare validation results, which hinders straightforward model selection based on prediction accuracy. It is hard to explain why so many metrics are being used, including some that were devised exclusively by the authors for a specific study. One possible explanation is that authors choose metrics which they believe make their model look successful. Some evidence supporting this hypothesis is the fact that some validation results are presented in vague terms, e.g. "less than" or "greater than" some value (Table 4). Moreover, no greenhouse model validation study ever seems to conclude that the model under investigation is poor, although positive results bias (Catalogue of Bias Collaboration, 2017) may also play a role here.

The use of research facilities for evaluating energy use predictions carries special difficulties, as research typically takes place in small compartments within a bigger greenhouse. Edge effects due to a relatively large wall surface area, heat transport between compartments, and a central heating system distributing heat to all compartments simultaneously, contribute error to the energy use measurements of individual compartments. These are all issues that are typically ignored in "perfectly stirred tank" type models, which often assume that the greenhouse is infinitely large (Section 2.1). Ideally, authors should report on the procedures taken to measure or estimate energy use in compartments, including what steps were taken to avoid edge effects.

Yield prediction was not part of the main focus of this study (Section 2.1), but several greenhouse climate models reported on it during model validation (Table 4). When evaluating yield predictions, one crucial component is the dry matter content (DMC) of the harvested product. This parameter converts dry weight predictions – as they typically appear in crop models – to fresh weight yield. In tomatoes, DMC ranges between 4 and 7.5% (Heuvelink et al., 2018), which results in a substantial range of yield predictions given a particular dry weight outcome: for 1 kg of dry weight, the range of 4–7.5% corresponds to a fresh weight prediction range of 13–25 kg. Thus, modifications within a generally accepted range of DMC can nearly double a given model's yield prediction. Ideally, authors would report on how they estimate DMC when comparing dry weight model outputs to fresh weight yield measurements.

At the same time, there is room to consider how accurate we can expect yield predictions for continuously yielding crops to really be. In practice, growers have some flexibility regarding the moment of harvest (Saltveit, 2018), and harvesting strategy, influenced by concerns such as labor availability or produce price, may have a major influence on harvest (Marcelis and Gijzen, 1998). As long as such concerns are not included in greenhouse models, it may be wiser to settle for longer term yield predictions (aggregated on a monthly or yearly basis) than to expect accurate daily or weekly yield predictions.

5.4.2. How accurate should process-based greenhouse climate models be?

The lack of standards in greenhouse model validation raises the question how accurate greenhouse climate models really need to be. One standard that began to establish regarding indoor greenhouse climate is that a rRMSE of up to 10% is acceptable (e.g., Ahamed et al., 2018a; Sethi et al., 2013; Vanthoor et al., 2011b), although this choice lacks justification. In particular, while rRMSE provides a convenient comparison between predictions in different units, it can also be misleading when comparing the same units under different settings. For example, an rRMSE of 10% corresponds to an RMSE of 1.5 °C when the mean temperature is 15 °C but to an RMSE of 3 °C when the mean temperature is 30 °C. The rRMSE is in fact unsuitable for non-absolute units such as °C: note that when the average temperature is 0 °C, the rRMSE is undefined (or infinite).

In any case, it is counterproductive to set a fixed metric where models achieving values above or below some golden standard are deemed useful or useless. This lesson was painfully learned for the case of statistical significance and *p*-values (Wasserstein and Lazar, 2016). Nevertheless, some guidelines may be useful here: a model cannot be expected to be more accurate than the variance that is already present in the system, including measurement error. For instance, we cannot expect indoor climate predictions to be more accurate than the sensors used for measurements. Greenhouse climate sensors often demonstrate considerable measurement errors, which exceed the desired standards set for the industry, even after sensor maintenance and calibration (Bontsema et al., 2011). For example, the measurement error for indoor air temperature was found in one case to be in the range of 0.04–0.45 °C (Bontsema et al., 2011).

It would also be helpful if validation studies would provide information that helps distinguish between systematic and random errors in their predictions. For example, a model that provides accurate indoor climate predictions, but with a time delay compared to the measured data, may be an extremely useful model but it would still produce a poor RMSE. Reporting on autocorrelation, bias, and other metrics of the error is more nuanced than a simple yes or no answer to the question of whether a model is valid, but it provides considerable insight to potential users of the model. Naturally, publicly sharing the validation data, including measurements, predictions, and record of control actions, would allow potential users to test the validation results using whatever metrics they like. However, sharing such data is extremely rare.

Similarly, it would be useful to evaluate model errors with respect to the spatial variance that naturally exists in the greenhouse climate. As shown by Van Beveren et al. (2015a), indoor air temperatures can differ by nearly 2 °C, within the same horizontal plane.

At the same time, it should be stressed that models are a means to an end, and the goal of achieving perfect model predictions is not very useful in and of itself. Model accuracy should be evaluated with respect to the particular goal the model is meant to serve. It would be worthwhile to reflect whether the model validation process properly serves this evaluation. Moreover, assuming modelling studies are meant to eventually guide and shape horticultural practice, some reflection on the consequences of model uncertainty on actual practice would be useful. For example, what is the practical meaning of inaccurate predictions of indoor climate, yield, or energy use? A discussion on these consequences would typically require some estimates on market prices, as well as other practical considerations such as resource availability. Nevertheless, such discussions would help carry modelling studies away from a purely theoretic realm, and place them within the context of the sector that they ideally should serve.

For instance, the acceptable error in models used for climate control might be very different from that of models used for system analysis. Accurate, high frequency predictions of the indoor climate may not be needed for models used in greenhouse structure design; for this goal, aggregation on bigger timescales is probably more suitable.

5.4.3. Model parametrization

An important component of model development is setting the values for the model parameters. Parameter values may be based on previous literature, direct measurements, or calibration. Simple models typically have relatively fewer parameters, but those tend to lump together several processes in a way that is difficult to define or measure them directly.

Taking as an example two possible approaches for modelling transpiration (Section 2.4.6), Eq. 12 uses only 2 parameters, but those must be calibrated for any specific setting by dedicated measurements that correlate radiation with crop transpiration. Conversely, Eq. 13 includes 6 parameters, some of which are relatively easy to measure or to assume that they are within relatively narrow bands (e.g., the psychrometric constant), while others are much more difficult to estimate or measure directly (e.g., stomatal or aerodynamic conductance of a full crop).

Complex models tend to have more parameters, which increases the risk of correlation between parameters, making calibration difficult. At the same time, parameters in complex models often express directly measurable or known values. Simple models often include fewer parameters, but those must be obtained through calibration. Considering the fact that data used for calibration should typically be separate from the data used for validation (Wallach et al., 2019a), and the general scarcity of available data (Section 4.4), calibration of models, both simple and complex, is often a challenging task.

Nevertheless, there is room to consider the influence of any particular parameter on total model performance. A sensitivity analysis can help determine how a particular parameter influences model output, and which parameters should be calibrated or measured (Wallach et al., 2019b). In any case, the objective of any given modelling study should stand at the center of how parameters are chosen. A certain parameter may be extremely influential for a particular objective but almost inconsequential for another. It is also important to clarify which parametrization choices were made, and the motivations behind them.

Unfortunately, model developers often give very little information about this process. For examples, if direct measurements are performed to estimate parameters, it would be helpful to report not only on the mean values obtained, but also on the parameter likelihood distribution. This uncertainty in the parameter values could then be taken into account when evaluating the complete model.

5.5. What advances in greenhouse modelling can we expect in the future?

5.5.1. Model development and extension

Ideally, and as already stated decades ago (Lacroix and Zanghi, 1990; Van Bavel et al., 1985), more efforts would be placed on improving the knowledge of individual processes in the greenhouse rather than reproduce existing models. For example, considerable efforts are currently being made in the modelling of CSGs. It would be worthwhile to test whether assumptions that were used when designing models for Venlo-type greenhouses (e.g., an "infinite greenhouse") still apply for CSG models. Similarly, there is a growing interest in modelling supplemental lighting in greenhouses, as new technologies such as LEDs are rapidly advancing. Unfortunately, very few studies provide systemic measurements of lamp output and its influence on the greenhouse energy and other balances (Nelson and Bugbee (2015) is one rare example). This issue is becoming increasingly important as plant physiologists learn about the responses of crops to narrow-band LED spectrums with the hopes of implementing these insights in greenhouses (Lazzarin et al., 2021; Ouzounis et al., 2015).

Other components of the greenhouse system which could use more development are mechanical cooling and dehumidification, where some advances have been made (De Zwart and Kempkes, 2008; Van Beveren et al., 2015a; Vanthoor et al., 2011b) but complete model descriptions and validation studies are still rare. The crop is an important component of the greenhouse climate, both for estimating photosynthesis and the system performance in terms of yield. In this respect, there remains a need for reliable quantitative information. For example, quantitative knowledge on the influence of adverse climate on crop behavior is limited (Vanthoor et al., 2011a). There is also very little quantitative knowledge on the influence of the indoor climate on the occurrence and spread of disease, although some work has been done, particularly regarding the prevention of botrytis (Baptista, 2007; Baptista et al., 2012; Cañadas et al., 2017; Körner et al., 2014). Furthermore, models describing the influence of irrigation water on the crop (e.g., Jiang et al., 2019) are rarely included in greenhouse models. In particular, dry matter content (DMC) remains an elusive but extremely important variable with very few studies attempting to accurately predict it. Other underdeveloped components in greenhouse crop models were noted by Marcelis et al. (1998) and include product quality, leaf area development, maintenance respiration and organ abortion.

An interesting feature of practically all detailed process-based greenhouse models is the fact that stomatal conductance is modelled separately for transpiration and photosynthesis. Stomata simultaneously regulate the exchange of water vapor and CO_2 between the air and the crop, and this principle lies at the basis of stomatal modelling (Buckley, 2017). This principle is often overlooked in greenhouse modelling. On the one hand this may be expected, as many models do not include a CO_2 balance (Table 3). But even when the CO_2 balance is absent, many process-based transpiration models are based on a prediction of stomatal behavior (Katsoulas and Stanghellini, 2019). For these models, it would be informative to test how the modelled stomatal behavior influences photosynthesis and crop growth, especially in models that have detailed descriptions of both transpiration and photosynthesis (e.g., Golzar et al., 2018; Vanthoor et al., 2011a; Vanthoor et al., 2011b).

5.5.2. Model transparency and comparison

Forty years ago, in the context of geographical models, Willmott (1981) lamented that "far too few computer programs have been published, resulting in the development of numerous overlapping and/or redundant algorithms". Unfortunately, this statement is still true for greenhouse climate models. Source code for greenhouse models is rarely made available by its authors, with a few exceptions emerging in the last years (Altes-Buch et al., 2019; Katzin et al., 2020b; Körner and Holst, 2017). The models for Ahamed et al. (2018a, 2018b, 2018c, 2019) are available in PDF form in Ahamed, 2018, providing transparency to the studies but limiting reuse due to copyright. This state of affairs is a far cry from that of agricultural models, where several long-standing models have made their code available, albeit with differing levels of accessibility (Soltani and Sinclair, 2015).

Accessible model code would not only facilitate model reuse and extension, it could also help to compare different models, evaluate their validity in different scenarios, learn about the strengths and weaknesses of each approach, and combine successful parts for further improvement. In arable farming, such efforts have been ongoing in projects such as the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013) and the Agricultural Model Exchange Initiative (AMEI) (Midingoyi et al., 2020).

An important component of model development and intercomparison is the development of benchmark datasets. Such datasets have been made available for crop model validation and comparison (Asseng et al., 2015). Indeed, publicly available shared datasets would help evaluate models by comparing their prediction accuracy in equivalent scenarios. Using such data, benchmark problems could be devised, setting quantitative and qualitative standards that are expected of greenhouse climate models. Unfortunately, publicly available data from greenhouses is extremely scarce. Some exceptions are the Autonomous Greenhouse Challenge (Hemming et al., 2019a, 2020) and the recently established Controlled Environment Agriculture Open Data initiative (CEAOD, 2020). Nevertheless, publicly available long-term data from large-scale commercial greenhouses is currently missing.

5.5.3. Model selection

The models explored in this study are in their core essentially the same. All models describe similar key variables, and include processes derived from basic laws of physics concerning the conservation of mass and energy. Nevertheless, the models differ in the details of the individual parameters and transport phenomena described. Ideally, the choice of these details should depend on a specific study's objectives and goals. Unfortunately, the reasoning behind the choices made during model development, or a thorough analysis of the pros and cons of these choices, is largely left undocumented.

The overview given in this study could help greenhouse modelers reflect on the issues faced in model selection and development, and consider the range of suitability, complexity, validity, and transparency of their model. While the models included in this review are only a small part of the vast range of greenhouse climate models that have been developed, this study provides an initial point of reference and directs researchers to consider several aspects, both when choosing an existing model to build on and when presenting their own work.

An alternative approach to model selection is the use of multimodel ensembles. In this approach, multiple models are used in parallel to predict a certain outcome. The range, variability, and average of the model predictions can provide valuable insights on the system being modelled and on the models used to predict its performance. This approach has been tried in the context of crop modelling, producing some promising results (Martre et al., 2015; Wallach et al., 2018).

When developing new models, developers should explore which models already exist that describe the system they are interested in, such as the type of greenhouse, crop, and equipment included in their system. Developers should consider the objectives of previous models and reflect critically whether using a given model is suitable to satisfy their own objectives. Model validation studies are useful for demonstrating whether a given model accurately represents a particular system. At the same time, the structure and assumptions underlying the model are equally important for judging the suitability of a model for a particular goal.

The points above are also crucial in the reporting on model developments. Ideally, developers would clearly indicate the type of system (greenhouse structure, crop, equipment, climate) they have in mind when designing a model. The reasons for developing and using a model should be clearly stated, as well as the assumptions used and results from previous works included in the model. Lastly, model transparency, inclusion of model code and sharing of data would greatly facilitate model reuse and advancement and will help push forward the entire field of greenhouse modelling, and greenhouse horticulture in general.

6. Conclusion

This review surveyed process-based greenhouse climate models published in the years 2018–2020, in an effort to explain the proliferation of greenhouse models and the variation between them. This outlining of the current state of greenhouse modelling can serve as a starting point for reflection, both for researchers reporting on their own models, and for the greenhouse modelling community as a whole. Regarding the current state of greenhouse modelling, the following key results were found:

- There is a tendency in greenhouse modelling to develop new models rather than extend or reuse existing models. Model reuse or extension of existing models is typically reserved to cases where researchers are building upon their own models, or when very simple models are reused. Models differ in the type of greenhouse and crop they describe, the equipment included, and in their research objectives, but there is also considerable overlap and redundancy between the various published models.
- Process-based greenhouse climate models share a general common structure, but they vary considerably in the choice of components that are included in the model, and in the treatment of each component. Depending on the modelling approach and objectives, each component can be completely neglected, represented with a single empirical function, or described with a process-based submodel which includes the influence of multiple factors. However, due to a lack of common evaluation standards, it is difficult to assess the benefits and drawbacks of each modelling approach.
- Extension and reuse of models is largely limited to developers extending their own models, except in the case of relatively simple models. A possible reason for this circumstance is the lack of transparency and availability of existing models, which makes it difficult to build on them.
- There is a lack of consensus in greenhouse modelling regarding how models should be evaluated, the type and size of datasets that should be used, the appropriate metrics for validation, or the required accuracy for a particular application.

In view of this current state affairs, we encourage model developers to reflect on, and explicitly state, their models' range of suitability (what questions can it help answer?), complexity (how many processes and time scales do they include, and why?), validity (under which circumstances has the model been evaluated?), and transparency (how can others reuse or extend the knowledge embodied in the model?). Regarding the greenhouse modelling community as a whole, we hope that the slowly emerging trends of publicly shared datasets and source code will continue, and that these will help facilitate model integration, extension, reuse and comparison. Together with the establishment of common benchmark tests and validation standards, the modelling community can play an invaluable role in the advancement of the greenhouse sector towards efficient and safe production in an age of climate change and uncertainty.

Funding sources

The research described in this article was part of the "LED it be 50%" Perspectief program number 14217, supported by the Netherlands Organization for Scientific Research - Domain Applied and Engineering Sciences (NWO-AES), Glastuinbouw Nederland, Signify, B-Mex, and Ridder Growing Solutions.

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.

Acknowledgments

The authors would like to thank Ambra Tosto for help in formulating the early stages of the manuscript, Cécile Levrault for translations from French, Ep Heuvelink for a discussion on crop yield predictions, and Selwin Hageraats for insights on R^2. We would also like to thank the anonymous reviewers for their helpful thoughts and comments.

References

Abbes, M., Farhat, A., Mami, A., Dauphin-Tanguy, G., 2010. Pseudo bond graph model of coupled heat and mass transfers in a plastic tunnel greenhouse. Simul. Model. Pract. Theory 18 (9), 1327–1341. https://doi.org/10.1016/j.simpat.2010.05.006.

Abbes, M., Farhat, A., Mami, A., 2019. Pseudo bond graph tunnel greenhouse model with accurate longwave/shortwave radiations model. Math. Comput. Model. Dyn. Syst. 25 (1), 90–114. https://doi.org/10.1080/13873954.2018.1555172.

Addor, N., Melsen, L.A., 2019. Legacy, rather than adequacy, drives the selection of hydrological models. Water Resour. Res. 55 (1), 378–390. https://doi.org/10.1029/2018WR022958.

Ahamed, M.S., 2018. Thermal environment modeling and optimization of greenhouse in cold regions. University of Saskatchewan.

Ahamed, M.S., Guo, H., Tanino, K., 2018a. Development of a thermal model for simulation of supplemental heating requirements in Chinese-style solar greenhouses. Comput. Electron. Agric. 150 (January), 235–244. https://doi.org/10.1016/j.compag.2018.04.025.

Ahamed, M.S., Guo, H., Tanino, K., 2018b. A quasi-steady state model for predicting the heating requirements of conventional greenhouses in cold regions. Information Processing in Agriculture 5 (1), 33–46. https://doi.org/10.1016/j.inpa.2017.12.003.

Ahamed, M.S., Guo, H., Tanino, K., 2018c. Energy-efficient design of greenhouse for Canadian prairies using a heating simulation model. Int. J. Energy Res. 42 (6), 2263–2272. https://doi.org/10.1002/er.4019.

Ahamed, M.S., Guo, H., Tanino, K., 2018d. Sensitivity analysis of CSGHEAT model for estimation of heating consumption in a Chinese-style solar greenhouse. Comput. Electron. Agric. 154, 99–111. https://doi.org/10.1016/j.compag.2018.08.040.

Ahamed, M.S., Guo, H., Tanino, K., 2019. Energy saving techniques for reducing the heating cost of conventional greenhouses. Biosyst. Eng. 178, 9–33. https://doi.org/10.1016/j.biosystemseng.2018.10.017.

Ahamed, M.S., Guo, H., Tanino, K., 2020. Modeling heating demands in a Chinese-style solar greenhouse using the transient building energy simulation model TRNSYS. Journal of Building Engineering 29, 101114. https://doi.org/10.1016/j.jobe.2019.101114.

Albright, L.D., Seginer, I., Marsh, L.S., Oko, A., 1985. In situ thermal calibration of unventilated greenhouses. J. Agric. Eng. Res. 31 (3), 265–281. https://doi.org/10.1016/0021-8634(85)90093-9.

Albright, L.D., Gates, R.S., Arvanitis, K.G., Drysdale, A.E., 2001. Environmental control for plants on earth and in space. IEEE Control. Syst. Mag. 21 (5), 28–47. https://doi.org/10.1109/37.954518.

Alinejad, T., Yaghoubi, M., Vadiee, A., 2020. Thermo-environomic assessment of an integrated greenhouse with an adjustable solar photovoltaic blind system. Renew. Energy 156, 1–13. https://doi.org/10.1016/j.renene.2020.04.070.

Altes-Buch, Q., Quoilin, S., Lemort, V., 2019. Greenhouses: A Modelica library for the simulation of greenhouse climate and energy systems. In: Proceedings of the 13th international Modelica conference, Regensburg, Germany, March 4–6, 2019, 157, pp. 533–542. https://doi.org/10.3384/ecp19157533.

Antle, J.M., Stoorvogel, J.J., Valdivia, R.O., 2014. New parsimonious simulation methods and tools to assess future food and environmental security of farm populations. Philosophical Transactions of the Royal Society B: Biological Sciences 369 (1639). https://doi.org/10.1098/rstb.2012.0280.

Asseng, S., Ewert, F., Martre, P., Rosenzweig, C., Jones, J.W., Hatfield, J., Ruane, A., Boote, K.J., Thorburn, P.J., Rötter, R.P., Cammarano, D., Brisson, N., Basso, B., Aggarwal, P.K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A.J., Doltra, J., Wolf, J., 2015. Benchmark data set for wheat growth models: field experiments and AgMIP multi-model simulations. Open Data Journal for Agricultural Research 1, 1–5.

Baglivo, C., Mazzeo, D., Panico, S., Bonuso, S., Matera, N., Congedo, P.M., Oliveti, G., 2020. Complete greenhouse dynamic simulation tool to assess the crop thermal well-being and energy needs. Appl. Therm. Eng. 179, 115698 https://doi.org/10.1016/j.applthermaleng.2020.115698.

Baptista, F.J., 2007. Modelling the Climate in Unheated Tomato Greenhouses and Predicting Botrytis Cinerea Infection. Universidade de Évora.

Baptista, F.J., Bailey, B.J., Meneses, J.F., 2012. Effect of nocturnal ventilation on the occurrence of Botrytis cinerea in Mediterranean unheated tomato greenhouses. Crop Prot. 32, 144–149. https://doi.org/10.1016/j.cropro.2011.11.005.

Bellocchi, G., Rivington, M., Donatelli, M., Matthews, K., 2010. Validation of biophysical models: issues and methodologies. A review. *Agronomy for Sustainable Development* 30 (1), 109–130. https://doi.org/10.1051/agro/2009001.

Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., Marsili-Libelli, S., Newham, L.T.H., Norton, J.P., Perrin, C., Pierce, S. A., Robson, B., Seppelt, R., Voinov, A.A., Fath, B.D., Andreassian, V., 2013. Characterising performance of environmental models. Environ. Model. Softw. 40, 1–20. https://doi.org/10.1016/j.envsoft.2012.09.011.

Blasco, X., Martínez, M., Herrero, J.M., Ramos, C., Sanchis, J., 2007. Model-based predictive control of greenhouse climate for reducing energy and water consumption. Comput. Electron. Agric. 55 (1), 49–70. https://doi.org/10.1016/j.compag.2006.12.001.

B-Mex, 2020. About B-Mex. https://b-mex.nl/OverOns.html.

Bontsema, J., Hemming, J., Stanghellini, C., De Visser, P.H.B., Van Henten, E.J., Budding, J., Rieswijk, T., Nieboer, S., 2007. On-line estimation of the transpiration in greenhouse horticulture. Proceedings Agricontrol 3–5.

Bontsema, J., Van Henten, E.J., Gieling, T.H., Swinkels, G.L.A.M., 2011. The effect of sensor errors on production and energy consumption in greenhouse horticulture. Comput. Electron. Agric. 79 (1), 63–66. https://doi.org/10.1016/j.compag.2011.08.008.

Bot, G.P.A., 1983. Greenhouse Climate: From Physical Processes to a Dynamic Model.

Boulard, T., Baille, A., 1987. Analysis of thermal performance of a greenhouse as a solar collector. Energy in Agriculture 6 (1), 17–26. https://doi.org/10.1016/0167-5826(87)90018-0.

Boulard, T., Draoui, B., Neirac, F., 1996. Calibration and validation of a greenhouse climate control model. Acta Horticulturae 406, 49–61. https://doi.org/10.17660/actahortic.1996.406.4.

Boulard, T., Kittas, C., Roy, J.C., Wang, S., 2002. Convective and ventilation transfers in greenhouses, part 2: determination of the distributed greenhouse climate. Biosyst. Eng. 83 (2), 129–147. https://doi.org/10.1006/bioe.2002.0114.

Buckley, T.N., 2017. Modeling stomatal conductance. Plant Physiol. 174 (June) https://doi.org/10.1104/pp.16.01772.

Businger, J.A., 1963. The glasshouse (greenhouse) climate. In: Van Wijk, W.R. (Ed.), Physics of Plant Environment. North-Holland, pp. 277–318.

Cañadas, J., Sánchez-Molina, J.A., Rodríguez, F., del Águila, I.M., 2017. Improving automatic climate control with decision support techniques to minimize disease effects in greenhouse tomatoes. Information Processing in Agriculture 4 (1), 50–63. https://doi.org/10.1016/J.INPA.2016.12.002.

Cao, H.X., Hanan, J.S., Liu, Y., Liu, Y.X., Yue, Y. Bin, Zhu, D.W., Lu, J.F., Sun, J.Y., Shi, C. L., Ge, D.K., Wei, X.F., Yao, A.Q., Tian, P.P., Bao, T.L., 2012. Comparison of crop model validation methods. J. Integr. Agric. 11 (8), 1274–1285. https://doi.org/10.1016/S2095-3119(12)60124-5.

Catalogue of Bias Collaboration, Plüddemann, A., Banerjee, A., O'Sullivan, J., 2017. Positive results bias. Catalogue Of Biases. https://www.catalogueofbiases.org/biases/positive-results-bias.

CEAOD, 2020. Controlled Environment Agriculture Open Data. https://ceaod.github.io/.

Chen, J., Zhao, J., Xu, F., Hu, H., Ai, Q., Yang, J., 2015. Modeling of energy demand in the greenhouse using PSO-GA hybrid algorithms. Math. Probl. Eng. 2015 https://doi.org/10.1155/2015/871075.

Chen, J., Yang, J., Zhao, J., Xu, F., Shen, Z., Zhang, L., 2016. Energy demand forecasting of the greenhouses using nonlinear models based on model optimized prediction method. Neurocomputing 174, 1087–1100. https://doi.org/10.1016/j.neucom.2015.09.105.

Chen, J., Xu, F., Ding, B., Wu, N., Shen, Z., Zhang, L., 2019a. Performance analysis of radiation and electricity yield in a photovoltaic panel integrated greenhouse using the radiation and thermal models. Comput. Electron. Agric. 164 https://doi.org/10.1016/j.compag.2019.104904.

Chen, C., Yu, N., Yang, F., Mahkamov, K., Han, F., Li, Y., Ling, H., 2019b. Theoretical and experimental study on selection of physical dimensions of passive solar greenhouses for enhanced energy performance. Sol. Energy 191, 46–56. https://doi.org/10.1016/j.solener.2019.07.089.

Choab, N., Allouhi, A., El Maakoul, A., Kousksou, T., Saadeddine, S., Jamil, A., 2019. Review on greenhouse microclimate and application: design parameters, thermal modeling and simulation, climate controlling technologies. Sol. Energy 191, 109–137. https://doi.org/10.1016/j.solener.2019.08.042.

Crout, N.M.J., Tarsitano, D., Wood, A.T., 2009. Is my model too complex? Evaluating model formulation using model reduction. Environ. Model. Softw. 24 (1), 1–7. https://doi.org/10.1016/j.envsoft.2008.06.004.

De Halleux, D., 1989. Modèle dynamique des échanges énergétiques des serres: étude théorique et expérimentale. Gembloux, Belgium.

De Ridder, F., Van Roy, J., Vanlommel, W., Van Calenberge, B., Vliex, M., De Win, J., De Schutter, B., Binnemans, S., De Pauw, M., 2020. Convex parameter estimator for grey-box models, applied to characterise heat flows in greenhouses. Biosyst. Eng. 191, 13–26. https://doi.org/10.1016/j.biosystemseng.2019.12.009.

De Zwart, H.F., 1993. Determination of direct transmission of a multispan greenhouse using vector algebra. J. Agric. Eng. Res. 56, 39–49. https://doi.org/10.1006/jaer.1993.1059.

De Zwart, H.F., 1996. Analyzing Energy-Saving Options in Greenhouse Cultivation Using a Simulation Model. Landbouwuniversiteit, Wageningen.

De Zwart, H.F., Kempkes, F., 2008. Characterizing of cooling equipment for closed greenhouses. Acta Hortic. 801, 409–415. https://doi.org/10.17660/actahortic.2008.801.43.

Draoui, B., 1994. Caractérisation et analyse du comportement thermohydrique d'une serre horticole. L'université de Nice Sophia Antipolis.

Duncan, W.G., Maize, L., Evans, T., 1975. Crop Physiology - some Case Histories 374. Cambridge University Press.

Eker, S., Rovenskaya, E., Obersteiner, M., Langan, S., 2018. Practice and perspectives in the validation of resource management models. Nat. Commun. 9 (1), 1–10. https://doi.org/10.1038/s41467-018-07811-9.

Esmaeli, H., Roshandel, R., 2017. Thermal model development for solar greenhouse considering climate condition. Proceedings of 1–12. https://doi.org/10.18086/swc.2017.26.04. SWC2017/SHC2017.

Esmaeli, H., Roshandel, R., 2020. Optimal design for solar greenhouses based on climate conditions. Renew. Energy 145, 1255–1265. https://doi.org/10.1016/j.renene.2019.06.090.

Evangelisti, L., Guattari, C., Asdrubali, F., 2019. On the sky temperature models and their influence on buildings energy performance: A critical review. Energy and Buildings 183, 607–625. https://doi.org/10.1016/J.ENBUILD.2018.11.037.

Forrester, J.W., 1961. Industrial Dynamics. MIT Press.

Gary, C., Jones, J.W., Tchamitchian, M., 1998. Crop modelling in horticulture: state of the art. Sci. Hortic. 74 (1), 3–20. https://doi.org/10.1016/S0304-4238(98)00080-6.

Garzoli, K., 1985. A simple greenhouse climate model. In. Acta Hortic. 174, 393–400.

Gharghory, S.M., 2020. Deep network based on long short-term memory for time series prediction of microclimate data inside the greenhouse. Int. J. Comput. Intell. Appl. 19 (02), 2050013. https://doi.org/10.1142/S1469026820500133.

Golzar, F., Heeren, N., Hellweg, S., Roshandel, R., 2018. A novel integrated framework to evaluate greenhouse energy demand and crop yield production. Renew. Sust. Energ. Rev. 96, 487–501. https://doi.org/10.1016/j.rser.2018.06.046.

Golzar, F., Heeren, N., Hellweg, S., Roshandel, R., 2019. A comparative study on the environmental impact of greenhouses: A probabilistic approach. Sci. Total Environ. 675, 560–569. https://doi.org/10.1016/j.scitotenv.2019.04.092.

Goudriaan, J., Van Laar, H.H., 1993. Modelling potential crop growth processes: Textbook with exercises. In: Current Issues in Production Ecology, vol. 2. Kluwer Academic Publishers. https://doi.org/10.1017/CBO9781107415324.004.

Haefner, J.W., 2005. Qualitative model formation. In: Modeling Biological Systems: Principles and Applications, 2nd ed. Springer Science+Business Media.

Hammer, G., Messina, C., Wu, A., Cooper, M., 2019. Biological reality and parsimony in crop models—why we need both in crop improvement! In Silico Plants 1 (1). https://doi.org/10.1093/insilicoplants/diz010.

Hasni, A., Taibi, R., Draoui, B., Boulard, T., 2011. Optimization of greenhouse climate model parameters using particle swarm optimization and genetic algorithms. Energy Procedia 6, 371–380. https://doi.org/10.1016/j.egypro.2011.05.043.

Hemming, S., De Zwart, H.F., Elings, A., Righini, I., Petropoulou, A., 2019a. Autonomous greenhouse challenge, first edition (2018). 4TU.Centre for Research Data. Dataset. https://doi.org/10.4121/uuid:e4987a7b-04dd-4c89-9b18-883aad30ba9a.

Hemming, S., De Zwart, H.F., Elings, A., Righini, I., Petropoulou, A., 2019b. Remote control of greenhouse vegetable production with artificial intelligence—greenhouse climate, irrigation, and crop production. Sensors 19 (8), 1807. https://doi.org/10.3390/s19081807.

Hemming, S., De Zwart, H.F., Elings, A., Petropoulou, A., Righini, I., 2020. Autonomous greenhouse challenge, second edition (2019). 4TU.ResearchData. https://doi.org/10.4121/uuid:88d22c60-21b3-4ea8-90db-20249a5be2a7.

Heuvelink, E., Li, T., Dorais, M., 2018. Crop growth and yield. In: Heuvelink, E. (Ed.), Tomatoes, 2nd ed. Cabi, pp. 89–135. https://doi.org/10.1079/9781780641935.0000.

Hikosaka, K., Niinemets, Ü., Anten, N.P.R., 2016. Canopy photosynthesis: from basics to applications. In: Hikosaka, K., Niinemets, Ü., Anten, N.P.R. (Eds.), Canopy Photosynthesis: From Basics to Applications SE - 6, vol. 42. https://doi.org/10.1007/978-94-017-7291-4_6.

Hölscher, T., 1992. Ein simulationsmodell für das gewächshausklima. University of Hannover.

Holzworth, D.P., Snow, V., Janssen, S., Athanasiadis, I.N., Donatelli, M., Hoogenboom, G., White, J.W., Thorburn, P., 2015. Agricultural production systems modelling and software: current status and future prospects. Environ. Model Softw. 72, 276–286. https://doi.org/10.1016/j.envsoft.2014.12.013.

Hoogendoorn Growth Management, 2020. Harvest Forecast. https://www.hoogendoorn.nl/en/product/harvest-forecast/.

Iddio, E., Wang, L., Thomas, Y., McMorrow, G., Denzer, A., 2020. Energy efficient operation and modeling for greenhouses: A literature review. Renew. Sust. Energ. Rev. 117, 109480 https://doi.org/10.1016/j.rser.2019.109480.

Janssen, S.J.C., Porter, C.H., Moore, A.D., Athanasiadis, I.N., Foster, I., Jones, J.W., Antle, J.M., 2017. Towards a new generation of agricultural system data, models and knowledge products: information and communication technology. Agric. Syst. 155, 200–212. https://doi.org/10.1016/j.agsy.2016.09.017.

Jarvis, P.G., 1976. The interpretation of the variations in leaf water potential and stomatal conductance found in canopies in the field. Philosophical Transactions of the Royal Society of London. B 273, 593–610. https://doi.org/10.1098/RSTB.1976.0035.

Jiang, X., Zhao, Y., Wang, R., Zhao, S., 2019. Modeling the relationship of tomato yield parameters with deficit irrigation at different growth stages. HortScience 54 (9), 1492–1500. https://doi.org/10.21273/HORTSCI14179-19.

Jolliet, O., Danloy, L., Gay, J.B., Munday, G.L., Reist, A., 1991. HORTICERN: an improved static model for predicting the energy consumption of a greenhouse. Agric. For. Meteorol. 55 (3–4), 265–294. https://doi.org/10.1016/0168-1923(91)90066-Y.

Jomaa, M., Tadeo, F., Abbes, M., Abdelkader, M., 2019. Greenhouse modeling, validation and climate control based on fuzzy logic. Engineering, Technology & Applied Science Research 9 (4), 4405–4410.

Jones, J.W., Kenig, A., Vallejos, C.E., 1999. Reduced state-variable tomato growth model. Trans. Am. Soc. Agric. Eng. 42 (1994), 255–265.

Katsoulas, N., Stanghellini, C., 2019. Modelling crop transpiration in greenhouses: different models for different applications. Agronomy 9 (7), 392. https://doi.org/10.3390/agronomy9070392.

Katzin, D., Van Mourik, S., Kempkes, F., Van Henten, E.J., 2020a. Energy saving measures in optimally controlled greenhouse lettuce cultivation. Acta Hortic. 1271, 265–272. https://doi.org/10.17660/ActaHortic.2020.1271.36.

Katzin, D., Van Mourik, S., Kempkes, F., Van Henten, E.J., 2020b. GreenLight – an open source model for greenhouses with supplemental lighting: evaluation of heat requirements under LED and HPS lamps. Biosyst. Eng. 194, 61–81. https://doi.org/10.1016/j.biosystemseng.2020.03.010.

Keating, B.A., 2020. Crop, soil and farm systems models – science, engineering or snake oil revisited. Agric. Syst. 184, 102903 https://doi.org/10.1016/j.agsy.2020.102903.

Keating, B.A., Thorburn, P.J., 2018. Modelling crops and cropping systems - evolving purpose, practice and prospects. Eur. J. Agron. 100, 163–176. https://doi.org/10.1016/j.eja.2018.04.007.

Kobayashi, K., Salam, M.U., 2000. Comparing simulated and measured values using mean squared deviation and its components. Agron. J. 92 (March), 345–352. https://doi.org/10.1007/s100870050043.

Körner, O., 2019. Models, sensors and decision support systems in greenhouse cultivation. In: Marcelis, L.F.M., Heuvelink, E. (Eds.), Achieving Sustainable Greenhouse Production, 1st ed. Burleigh Dodds Science Publishing, pp. 379–412. https://doi.org/10.19103/AS.2019.0052.15.

Körner, O., Holst, N., 2017. An open-source greenhouse modelling platform. Acta Hortic. 1154, 241–248. https://doi.org/10.17660/ActaHortic.2017.1154.32.

Körner, O., Holst, N., De Visser, P.H.B., 2014. A model-based decision support tool for grey mould prediction. Acta Hortic. 1037, 569–574. https://doi.org/10.17660/ActaHortic.2014.1037.71.

Kuijpers, W.J.P., Van de Molengraft, M.J.G., Van Mourik, S., Van't Ooster, A., Hemming, S., Van Henten, E.J., 2019. Model selection with a common structure: tomato crop growth models. Biosyst. Eng. 187, 247–257. https://doi.org/10.1016/j.biosystemseng.2019.09.010.

Kuijpers, W.J.P., Katzin, D., Van Mourik, S., Antunes, D.J., Hemming, S., Van de Molengraft, M.J.G., 2021. Lighting systems and strategies compared in an optimally controlled greenhouse. Biosyst. Eng. 202, 195–216. https://doi.org/10.1016/j.biosystemseng.2020.12.006.

Lacroix, R., Zanghi, J.C., 1990. Étude comparative de la structure des modèles de transfert d'énergie et de masse dans les serres. Can. Agric. Eng. 32, 269–284.

Lammari, K., Bounaama, F., Draoui, B., Mrah, B., Haidas, M., 2012. GA optimization of the coupled climate model of an order two of a greenhouse. Energy Procedia 18, 416–425. https://doi.org/10.1016/j.egypro.2012.05.053.

Lammari, K., Bounaama, F., Ouradj, B., Draoui, B., 2020. Constrained GA PI sliding mode control of indoor climate coupled MIMO greenhouse model. Journal of Thermal Engineering 6 (3), 313–326. https://doi.org/10.18186/THERMAL.711554.

Lazzarin, M., Meisenburg, M., Meijer, D., van Ieperen, W., Marcelis, L.F.M., Kappers, I.F., van der Krol, A.R., van Loon, J.J.A., Dicke, M., 2021. LEDs make it resilient: effects on plant growth and defense. Trends Plant Sci. 26 (5), 496–508. https://doi.org/10.1016/j.tplants.2020.11.013.

Legates, D.R., McCabe, G.J., 1999. Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. Water Resour. Res. 35 (1), 233–241. https://doi.org/10.1029/1998WR900018.

Lentz, W., 1998. Model applications in horticulture: a review. Sci. Hortic. 74 (1), 151–174. https://doi.org/10.1016/S0304-4238(98)00085-5.

Lopez-Cruz, I.L., Fitz-Rodríguez, E., Salazar-Moreno, R., Rojano-Aguilar, A., Kacira, M., 2018. Development and analysis of dynamical mathematical models of greenhouse climate : A review. Eur. J. Hortic. Sci. 83 (5), 269–280.

Ma, D., Carpenter, N., Maki, H., Rehman, T.U., Tuinstra, M.R., Jin, J., 2019. Greenhouse environment modeling and simulation for microclimate control. Comput. Electron. Agric. 162, 134–142. https://doi.org/10.1016/j.compag.2019.04.013.

Marcelis, L.F.M., Gijzen, H., 1998. Evaluation under commercial conditions of a model of prediction of the yield and quality of cucumber fruits. Sci. Hortic. 76, 171–181. https://doi.org/10.1016/S0304-4238(98)00156-3.

Marcelis, L.F.M., Heuvelink, E., Goudriaan, J., 1998. Modelling biomass production and yield of horticultural crops: A review. Sci. Hortic. 74 (1–2), 83–111. https://doi.org/10.1016/S0304-4238(98)00083-1.

Marcelis, L.F.M., Elings, A., De Visser, P.H.B., Heuvelink, E., 2009. Simulating growth and development of tomato crop. Acta Hortic. 821, 101–110. https://doi.org/10.17660/ActaHortic.2009.821.10.

Marcelis, L.F.M., Costa, J.M., Heuvelink, E., 2019. Achieving sustainable greenhouse production: present status, recent advances and future developments. In: Marcelis, L. F.M., Heuvelink, E. (Eds.), Achieving Sustainable Greenhouse Production. Burleigh Dodds Science Publishing, pp. 1–14. https://doi.org/10.19103/AS.2019.0052.01.

Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J.W., Rötter, R.P., Boote, K.J., Ruane, A.C., Thorburn, P.J., Cammarano, D., Hatfield, J.L., Rosenzweig, C., Aggarwal, P.K., Angulo, C., Basso, B., Bertuzzi, P., Biernath, C., Brisson, N., Challinor, A.J., Wolf, J., 2015. Multimodel ensembles of wheat growth: many models are better than one. Glob. Chang. Biol. 21 (2), 911–925. https://doi.org/10.1111/gcb.12768.

Midingoyi, C.A., Pradal, C., Athanasiadis, I.N., Donatelli, M., Enders, A., Fumagalli, D., Garcia, F., Holzworth, D., Hoogenboom, G., Porter, C., Raynal, H., Thorburn, P., Martre, P., 2020. Reuse of process-based models: automatic transformation into many programming languages and simulation platforms. In Silico Plants. https://doi.org/10.1093/insilicoplants/diaa007.

Mohamed, S., Hameed, I.A., 2018. A GA-based adaptive neuro-fuzzy controller for greenhouse climate control system. Alexandria Engineering Journal 57, 773–779. https://doi.org/10.1016/j.aej.2014.04.009.

Mohammadi, B., Ranjbar, F., Ajabshirchi, Y., 2020. Exergoeconomic analysis and multi-objective optimization of a semi-solar greenhouse with experimental validation. Appl. Therm. Eng. 164, 114563 https://doi.org/10.1016/j.applthermaleng.2019.114563.

Monteith, J.L., 1965. Evaporation and environment. Symposia of the Society for Experimental Biology. Symposia of the Society for Experimental Biology 19, 205–234.

Monteith, J.L., 1996. The quest for balance in crop modeling. Agron. J. 88, 695–697.

Morris, L.G., Trickett, E.S., Vanstone, F.H., Wells, D.A., 1958. The limitation of maximum temperature in a glasshouse by the use of a water film on the roof. J. Agric. Eng. Res. 3, 121–130.

Nelson, J.A., Bugbee, B., 2014. Economic analysis of greenhouse lighting: light emitting diodes vs. High Intensity Discharge Fixtures. PLoS ONE 9 (6), e99010. https://doi.org/10.1371/journal.pone.0099010.

Nelson, J.A., Bugbee, B., 2015. Analysis of environmental effects on leaf temperature under sunlight, high pressure sodium and light emitting diodes. PLoS One 10 (10), e0138930. https://doi.org/10.1371/journal.pone.0138930.

Norton, T., Sun, D.-W., Grant, J., Fallon, R., Dodd, V., 2007. Applications of computational fluid dynamics (CFD) in the modelling and design of ventilation systems in the agricultural industry: A review. Bioresour. Technol. 98 (12), 2386–2414. https://doi.org/10.1016/j.biortech.2006.11.025.

Oreskes, N., Shrader-Frechette, K., Belitz, K., 1994. Verification, validation, and confirmation of numerical models in the earth sciences. Science 263 (5147), 641–646.

Ouzounis, T., Rosenqvist, E., Ottosen, C.O., 2015. Spectral effects of artificial light on plant physiology and secondary metabolism: A review. HortScience 50 (8), 1128–1135.

Pasgianos, G.D., Arvanitis, K.G., Polycarpou, P., Sigrimis, N., 2003. A nonlinear feedback technique for greenhouse environmental control. Comput. Electron. Agric. 40, 153–177. https://doi.org/10.1016/S0168-1699(03)00018-8.

Passioura, J., 1973. Sense and nonsense in crop simulation. J. Aust. Inst. Agric. Sci. 39 (3), 181–183.

Passioura, J., 1996. Simulation models: science, snake oil, education, or engineering? Agron. J. 88, 690–694.

Pérez-González, A., Begovich-Mendoza, O., Ruiz-León, J., 2018. Modeling of a greenhouse prototype using PSO and differential evolution algorithms based on a real-time LabViewTM application. Applied Soft Computing Journal 62, 86–100. https://doi.org/10.1016/j.asoc.2017.10.023.

Piscia, D., Muñoz, P., Panadès, C., Montero, J.I., 2015. A method of coupling CFD and energy balance simulations to study humidity control in unheated greenhouses. Comput. Electron. Agric. 115, 129–141. https://doi.org/10.1016/j.compag.2015.05.005.

Priva, 2019. Plantonomy helps big greenhouses scale up and give small greenhouses stability. https://www.meetphil.com/insights/plantonomy-helps-big-greenhouses-scale-up-and-give-small-greenhouses-stability.

Rabobank, 2018. World Vegetable Map 2018. https://research.rabobank.com/far/en/sectors/regional-food-agri/world_vegetable_map_2018.html.

Rasheed, A., Na, W.H., Lee, J.W., Kim, H.T., Lee, H.W., 2019. Optimization of greenhouse thermal screens for maximized energy conservation. Energies 12 (3592). https://doi.org/10.3390/en12193592.

Righini, I., Vanthoor, B., Verheul, M.J., Naseer, M., Maessen, H., Persson, T., Stanghellini, C., 2020. A greenhouse climate-yield model focussing on additional light, heat harvesting and its validation. Biosyst. Eng. 194, 1–15. https://doi.org/10.1016/j.biosystemseng.2020.03.009.

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J.M., 2013. The agricultural model Intercomparison and improvement project (AgMIP): protocols and pilot studies. Agric. For. Meteorol. 170, 166–182. https://doi.org/10.1016/j.agrformet.2012.09.011.

Roy, J.C., Boulard, T., Kittas, C., Wang, S., 2002. Convective and ventilation transfers in greenhouses, part 1: the greenhouse considered as a perfectly stirred tank. Biosyst. Eng. 83 (1), 1–20. https://doi.org/10.1006/bioe.2002.0107.

Saltveit, M.E., 2018. Postharvest biology and handling of tomatoes. In: Heuvelink, E. (Ed.), Tomatoes, 2nd ed. Cabi, pp. 314–336. https://doi.org/10.1079/9781780641935.0000.

Seginer, I., Van Beveren, P.J.M., Van Straten, G., 2018. Day-to-night heat storage in greenhouses: 3 co-generation of heat and electricity (CHP). Biosyst. Eng. 172, 1–18. https://doi.org/10.1016/j.biosystemseng.2018.05.006.

Seginer, I., Van Straten, G., Van Beveren, P.J.M., 2020a. Modelling evapotranspiration in off-line simulations of greenhouse climate control. Acta Hortic. 1296, 341–348. https://doi.org/10.17660/actahortic.2020.1296.44.

Seginer, I., Van Straten, G., Van Beveren, P.J.M., 2020b. Day-to-night heat storage in greenhouses: 4. Changing the environmental bounds. Biosystems Engineering 192, 90–107. https://doi.org/10.1016/j.biosystemseng.2020.01.005.

Sethi, V.P., 2019. Thermal modelling of asymmetric overlap roof greenhouse with experimental validation. International Journal of Sustainable Energy 38 (1), 24–36. https://doi.org/10.1080/14786451.2018.1424167.

Sethi, V.P., Sumathy, K., Lee, C., Pal, D.S., 2013. Thermal modeling aspects of solar greenhouse microclimate control: A review on heating technologies. Sol. Energy 96, 56–82. https://doi.org/10.1016/j.solener.2013.06.034.

Sinclair, T.R., Seligman, N., 2000. Criteria for publishing papers on crop modeling. Field Crop Res. 68 (3), 165–172. https://doi.org/10.1016/S0378-4290(00)00105-2.
Soltani, A., Sinclair, T.R., 2015. A comparison of four wheat models with respect to robustness and transparency: simulation in a temperate, sub-humid environment. Field Crop Res. 175, 37–46. https://doi.org/10.1016/j.fcr.2014.10.019.
Stanghellini, C., 1987. Transpiration of Greenhouse Crops: An Aid to Climate Management. Landbouwuniversiteit Wageningen.
Stanghellini, C., Bontsema, J., De Koning, A., Baeza, E.J., 2012. An algorithm for optimal fertilization with pure carbon dioxide in greenhouses. Acta Hortic. 952, 119–124. https://doi.org/10.17660/ActaHortic.2012.952.13.
Stanghellini, C., Van't Ooster, A., Heuvelink, E., 2019. Greenhouse Horticulture: Technology for Optimal Crop Production, 1st ed. Wageningen Academic Publishers. https://doi.org/10.3920/978-90-8686-879-7.
Stockle, C.O., 1992. Canopy photosynthesis and transpiration estimates using radiation interception models with different levels of detail. Ecol. Model. 60 (1), 31–44. https://doi.org/10.1016/0304-3800(92)90011-3.
Su, Y., Xu, L., Goodman, E.D., 2018. Nearly dynamic programming NN-approximation-based optimal control for greenhouse climate: A simulation study. Optimal Control Applications and Methods 39 (2), 638–662. https://doi.org/10.1002/oca.2370.
Subin, M.C., Singh, A., Kalaichelvi, V., Karthikeyan, R., Periasamy, C., 2020. Design and robustness analysis of intelligent controllers for commercial greenhouse. Mechanical Sciences 11 (2), 299–316. https://doi.org/10.5194/ms-11-299-2020.
Taki, M., Ajabshirchi, Y., Ranjbar, S.F., Rohani, A., Matloobi, M., 2016. Modeling and experimental validation of heat transfer and energy consumption in an innovative greenhouse structure. Information Processing in Agriculture 3 (3), 157–174. https://doi.org/10.1016/j.inpa.2016.06.002.
Taki, M., Rohani, A., Rahmati-Joneidabad, M., 2018. Solar Thermal Simulation and Applications in Greenhouse. In: Information Processing in Agriculture, vol. 5. China Agricultural University, pp. 83–113. https://doi.org/10.1016/j.inpa.2017.10.003.
Tap, F., 2000. Economics-Based Optimal Control of Greenhouse Tomato Crop Production. Wageningen University.
Tap, F., Van Willigenburg, G., Van Straten, G., Van Henten, E.J., 1993. Optimal control of greenhouse climate: computation of the influence of fast and slow dynamics. IFAC Proceedings Volumes 26 (2), 1147–1150. https://doi.org/10.1016/S1474-6670(17)48650-2.
Tchamitchian, M., Van Willigenburg, G., Van Straten, G., 1992. Short term dynamic optimal control of the greenhouse climate. Wageningen MRS Report 92 (3).
Thornley, J.H.M., France, J., 2007. Mathematical Models in Agriculture: Quantitative Methods for the Plant, Animal and Ecological Sciences, 2nd ed. CABI.
Tiwari, G.N., 2003. Greenhouse Technology for Controlled Environment. Alpha Science.
Tiwari, G.N., Goyal, R.K., 1998. Greenhouse Technology: Fundamentals, Design, Modelling and Applications. Narosa publishing house.
Udink ten Cate, A.J., 1983. Modelling and (Adaptive) Control of Greenhouse Climates. Wageningen University.
Vadiee, A., Martin, V., 2013. Energy analysis and thermoeconomic assessment of the closed greenhouse - the largest commercial solar building. Appl. Energy 102, 1256–1266. https://doi.org/10.1016/j.apenergy.2012.06.051.
Van Bavel, C.H.M., Takakura, T., Bot, G.P.A., 1985. Global comparison of three greenhouse climate models. Acta Horticulturae 174, 21–34. https://doi.org/10.17660/actahortic.1985.174.1.
Van Beveren, P.J.M., Bontsema, J., Van Straten, G., Van Henten, E.J., 2015a. Minimal heating and cooling in a modern rose greenhouse. Appl. Energy 137, 97–109. https://doi.org/10.1016/j.apenergy.2014.09.083.
Van Beveren, P.J.M., Bontsema, J., Van Straten, G., Van Henten, E.J., 2015b. Optimal control of greenhouse climate using minimal energy and grower defined bounds. Appl. Energy 159, 509–519. https://doi.org/10.1016/j.apenergy.2015.09.012.
Van Henten, E.J., 1994. Greenhouse Climate Management: An Optimal Control Approach. Wageningen University. https://doi.org/10.1016/S0308-521X(94)90280-1.
Van Henten, E.J., 2003. Sensitivity analysis of an optimal control problem in greenhouse climate management. Biosyst. Eng. 85 (3), 355–364. https://doi.org/10.1016/S1537-5110(03)00068-0.
Van Henten, E.J., Bontsema, J., 2009. Time-scale decomposition of an optimal control problem in greenhouse climate management. Control. Eng. Pract. 17 (1), 88–96. https://doi.org/10.1016/j.conengprac.2008.05.008.
Van Henten, E.J., Bontsema, J., Van Straten, G., 1997. Improving the efficiency of greenhouse climate control: an optimal control approach. Neth. J. Agric. Sci. 45, 109–125.
Van Mourik, S., 2008. Modelling and Control of Systems with Flow. University of Twente. https://doi.org/10.3990/1.9789036526173.
Van Ooteghem, R.J.C., 2007. Optimal Control Design for a Solar Greenhouse. Wageningen University.
Van Straten, G., Van Willigenburg, G., Van Henten, E.J., Van Ooteghem, R.J.C., 2010. Optimal Control of Greenhouse Cultivation. CRC Press.
Vanthoor, B., 2011. A Model Based Greenhouse Design Method. Wageningen University.
Vanthoor, B., De Visser, P.H.B., Stanghellini, C., Van Henten, E.J., 2011a. A methodology for model-based greenhouse design: part 2, description and validation of a tomato yield model. Biosyst. Eng. 110 (4), 378–395. https://doi.org/10.1016/j.biosystemseng.2011.08.005.
Vanthoor, B., Stanghellini, C., Van Henten, E.J., De Visser, P.H.B., 2011b. A methodology for model-based greenhouse design: part 1, a greenhouse climate model for a broad range of designs and climates. Biosyst. Eng. 110 (4), 363–377. https://doi.org/10.1016/j.biosystemseng.2011.06.001.
Vanthoor, B., Van Henten, E.J., Stanghellini, C., De Visser, P.H.B., 2011c. A methodology for model-based greenhouse design: part 3, sensitivity analysis of a combined greenhouse climate-crop yield model. Biosyst. Eng. 110 (4), 396–412. https://doi.org/10.1016/j.biosystemseng.2011.08.006.
Villarreal-Guerrero, F., Kacira, M., Fitz-Rodríguez, E., Kubota, C., Giacomelli, G.A., Linker, R., Arbel, A., 2012. Comparison of three evapotranspiration models for a greenhouse cooling strategy with natural ventilation and variable high pressure fogging. Sci. Hortic. 134, 210–221. https://doi.org/10.1016/J.SCIENTA.2011.10.016.
Von Zabeltitz, C., 1999. Greenhouse structures. In: Stanhill, G., Enoch, H.Z. (Eds.), Ecosystems of the World 20: Greenhouse Ecosystems, 1st ed. Elsevier, pp. 17–69.
Wallach, D., Martre, P., Liu, B., Asseng, S., Ewert, F., Thorburn, P.J., Van Ittersum, M.K., Aggarwal, P.K., Ahmed, M., Basso, B., Biernath, C., Cammarano, D., Challinor, A.J., De Sanctis, G., Dumont, B., Eyshi Rezaei, E., Fereres, E., Fitzgerald, G.J., Gao, Y., Zhang, Z., 2018. Multimodel ensembles improve predictions of crop-environment-management interactions. Glob. Chang. Biol. 24 (11), 5072–5083. https://doi.org/10.1111/gcb.14411.
Wallach, D., Makowski, D., Jones, J.W., Brun, F., 2019a. Model Evaluation. In: Working with Dynamic Crop Models, 3rd ed. Elsevier Academic Press, pp. 311–373. https://doi.org/10.1016/B978-0-12-811756-9.00009-5.
Wallach, D., Makowski, D., Jones, J.W., Brun, F., 2019b. Uncertainty and sensitivity analysis. In: Working with Dynamic Crop Models, 3rd ed. Elsevier Academic Press, pp. 209–250. https://doi.org/10.1016/b978-0-12-811756-9.00006-x.
Wasserstein, R.L., Lazar, N.A., 2016. The ASA statement on p -values: context, process, and purpose. Am. Stat. 70 (2), 129–133. https://doi.org/10.1080/00031305.2016.1154108.
Willmott, C.J., 1981. On the validation of models. Phys. Geogr. 2 (2), 184–194. https://doi.org/10.1080/02723646.1981.10642213.
Xu, D., Du, S., Van Willigenburg, G., 2018a. Adaptive two time-scale receding horizon optimal control for greenhouse lettuce cultivation. Comput. Electron. Agric. 146, 93–103. https://doi.org/10.1016/j.compag.2018.02.001.
Xu, D., Du, S., Van Willigenburg, G., 2018b. Optimal control of Chinese solar greenhouse cultivation. Biosyst. Eng. 171, 205–219. https://doi.org/10.1016/J.BIOSYSTEMSENG.2018.05.002.
Xu, D., Du, S., Van Willigenburg, G., 2019. Double closed-loop optimal control of greenhouse cultivation. Control. Eng. Pract. 85, 90–99. https://doi.org/10.1016/j.conengprac.2019.01.010.
Yang, J.M., Yang, J.Y., Liu, S., Hoogenboom, G., 2014. An evaluation of the statistical methods for testing the performance of crop models with observed data. Agric. Syst. 127, 81–89. https://doi.org/10.1016/j.agsy.2014.01.008.
Zhang, G., Ding, X., Li, T., Pu, W., Lou, W., Hou, J., 2020. Dynamic energy balance model of a glass greenhouse: an experimental validation and solar energy analysis. Energy 198, 117281. https://doi.org/10.1016/j.energy.2020.117281.