A generic tool for quantifying the energy requirements of glasshouse food production

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1. Introduction

It is projected that global food production will increase by 70% by 2050 due to population growth (FAO, 2011). Subsequently, significant stress is expected at all stages of food supply chains as attempts are made to satisfy this demand growth while also putting much stress on the associated resources. This will almost certainly lead to an increase in the energy consumption and carbon footprint of the food production sector. In alignment with the global status quo, the UK food sector is highly dependent on fossil fuels and there are ambitious targets to reducing carbon emissions (DECC and DEFRA, 2015). In this context, it is important to identify methods that can minimize the energy requirements and carbon intensity of related activities. Based on estimates provided in Carr et al. (2014) and DEEC and National Statistics (2015), the UK domestic food sector accounts for about 30% of the country’s total greenhouse gas emissions. Therefore, significant improvements in this sector can

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Quantifying the use of resources in food production and its environmental impact is key to identifying distinctive measures which can be used to develop pathways towards low-carbon food systems. In this paper, a first-principle modelling approach is developed, referred to as gThermaR (Glasshouse-Thermal Requirements). gThermaR is a generic tool that focuses on the energy requirements of protected heated production, by integrating holistic energy, carbon, and cost modelling, food production, data analytics and visualization. The gThermaR tool employs historic data from weather stations, growing schedules and requirements specific to grower and product needs (e.g. set-point temperatures, heating periods, etc.) in order to quantify the heating and cooling requirements of glasshouse food production. In the present paper, a case study is reported that employs a database compiled for the UK. Another relevant feature of the tool is that it can quantify the effects that spatial and annual weather trends can have on these heating and cooling requirements. The main contribution of this work, therefore, concerns the development a tool that can provide a simple integrated approach for performing a wide range of analyses relevant to the thermal requirements of heated glasshouses. The tool is validated through collaborations with industrial partners and showcased in a case study of a heated glasshouse in the UK, offering the capacity to benchmark and compare different glasshouse types and food growth processes. Results from the case study indicate that a significant reduction in the heating requirement and, therefore, carbon footprint, of the facility can be achieved by improving key design and operational parameters. Results indicate savings in the peak daily and annual heating requirements of 44–50% and 51–57% respectively, depending on the region where the glasshouse is located. This improvement is also reflected in the carbon emissions and operating costs for the different energy sources considered. Furthermore, the temporal variability/uncertainty of the annual energy requirements and of the peak daily energy requirements are found to be considerably lowered through improvements to the glasshouse attributes. Overall, gThermaR proves its value in quantifying and identifying key factors that have a significant impact on energy requirements of heated glasshouses. Such valuable outputs are invaluable for stakeholders in the food industry that have an interest in mapping the sustainability and mitigating the carbon footprint of their supply chain processes.

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have a substantial impact in achieving the country’s emissions targets (Markides, 2013). In terms of energy consumption, the UK food chain is responsible for about 18% of the country’s primary energy use (Tassou, 2014), and thus it can be argued that energy security and cost uncertainty makes the pursuit of methods to reduce energy consumption a necessity to benefit businesses, society, and the environment. Similarly, food retailers are becoming increasingly interested in the optimal design and operation of their buildings (Alvarado et al., 2016; Acha et al., 2018), decarbonization and the use of renewables (Mariaud et al., 2017), and the challenging task of mapping the footprint of their supply chains to improve their robustness (ASDA, 2017; Sainsbury’s, 2017; Tesco plc, 2017). This is because it is assumed that the stronger the supply chains are, the better the business longevity prospects are.

Moreover, the development of fast and refrigerated logistics has created a market where the public’s expectations to consume out-of-season fresh products has grown substantially (Jones, 2002). With this increasing demand, glasshouse food production has become a promising approach for (partially) satisfying out-of-season demand (in addition to imports). Naturally, heated glasshouse food production is more energy and carbon intensive per planted area than open-field production. Nevertheless, the energy-use differences between domestic open-field production and food imports are expected to vary depending on their respective sub-processes, such as heating and ventilation for cooling in glasshouses. Other factors with a significant impact are geographical location, ambient weather conditions, installed technologies, energy resource efficiency, and food production targets (Carlsson-Kanyama, 1997), as well as the characteristics of the production system. This complexity has led to a debate over which approach is more energy intensive between food importation and local food production (Carlsson-Kanyama, 1998, 1997; Garnett, 2008). In Papadopoulos and Hao (1997), the authors investigated the effect of the glasshouse cover material in three tomato glasshouses focusing on yields, energy requirements and productivity, whereas Gupta and Chandra (2002) focused on the effects of a glasshouse’s design on its energy requirements, with a particular interest in the shape and orientation of a glasshouse in India. Furthermore, carbon dioxide enrichment strategies were considered in Chalabi et al. (2002), which extended to the development of a glasshouse energy balance model, while the American Society of Agricultural and Biological Engineers presented engineering practices based on accepted methods for designing heating and cooling systems for glasshouses in ASABE (2008).

Furthermore, a model for the calculation of the energy requirements of glasshouses was also presented in Wass and Barrie (1984). This paper focused on the effect of glasshouse dimensions, temperature regimes and weather variations on energy requirements, while Ozkan et al. (2011a, 2011b), Papadopoulos and Hao (1997), Subić et al. (2015), Mariani et al. (2016), Luo et al. (2005) and Wass and Barrie (1984), in Papadopoulos and Hao (1997), the authors investigated the effect of the glasshouse cover material in three tomato glasshouses focusing on yields, energy requirements and productivity, whereas Gupta and Chandra (2002) focused on the effects of a glasshouse’s design on its energy requirements, with a particular interest in the shape and orientation of a glasshouse in India. Furthermore, carbon dioxide enrichment strategies were considered in Chalabi et al. (2002), which extended to the development of a glasshouse energy balance model, while the American Society of Agricultural and Biological Engineers presented engineering practices based on accepted methods for designing heating and cooling systems for glasshouses in ASABE (2008).

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Focusing on the prediction of internal environment parameters of glasshouses Vanthoor et al. (2011) presented a methodology for describing the effects of weather and glasshouse design parameters, thus predicting aspects such as temperature, CO₂ concentration and vapour pressure. Similarly, Luo et al. (2005) focused on the Chinese subtropical climate conditions for predicting the glasshouse's microclimate conditions for summer and winter periods. In addition, Luo et al. (2005) identified the impact of set temperature on energy consumption and crop mass production.

Going a step further, the study in Moreton and Rowley (2012) examined the techno-economic feasibility of biomass combined heat and power (CHP) for the provision of energy to commercial glasshouses, also considering the carbon reductions achievable by the use of biomass. The study concluded that biomass CHP systems are a promising technology for economically feasible emission reduction, however their feasibility is susceptible to the demanded heat-to-power ratio and their ability to match the glasshouse's demand profiles. Details of this matching of the heat-to-power ratio and heat-supply temperature settings of CHP systems to the seasonal variation in the heat demand (temperature and intermittency of the load) of different end-users and market energy-demand segments can be found in Oyewunmi et al. (2017). The use of geothermal water in glasshouses for the production of vegetables (tomato, pepper and cucumber) and flowers (calla, gerbera and roses) has also been studied, e.g. in Subić et al. (2015). The economic benefits from incorporating this technique were found to be most significant for the production of roses and tomatoes.

The environmental impact of glasshouse food production for different products was also studied in literature through Life Cycle Assessments (LCA) approaches (e.g. Cellura et al., 2012; Dias et al., 2017; Ntinas et al., 2017; Payen et al., 2015; Torrellas et al., 2013). In the study of Cellura et al. (2012), the environmental and energy performances of peppers, tomatoes, melons, zucchini and cherry tomatoes were investigated. It was found that glasshouses located in Southern Europe had lower energy requirements and global warming potential than glasshouses in Northern Europe due to the lack of use of heating systems. This shows the significance of heating requirements on the environmental footprint of products grown under auxiliary heating systems and their competition against products in other locations. Moreover, Torrellas et al. (2013) developed an environmental impact calculator specifically for glasshouse food production. The results of Torrellas et al. (2013) showed the importance of energy consumption required for heating through its identification as the main contributor in the glass greenhouse located in Central Europe scenario. Also, Payen et al. (2015) found that energy use required in France for growing tomatoes in heated glasshouses was responsible for being worse with respect to global warming and energy use than importing tomatoes grown without heating from Morocco, even when considering the food miles. Dias et al. (2017) also studied through an LCA the sustainability of greenhouse tomato production in Ontario. Similar to the aforementioned studies, heating with fossil fuels was found to be the main contributor towards cumulative energy demand and global warming. Ntinas et al. (2017) studied the cumulative energy demand and carbon footprint of several scenarios for both open-field and greenhouse tomatoes production systems in Southern and Central Europe. Once again, the importance of heating fuel consumption in heated glasshouses was pointed out.

Besides the type of production system, the season can also have a substantial impact on the carbon footprint of greenhouse production (Page et al., 2012), stressing the importance of considering heating/growing schedules. Torrellas et al. (2012) investigated both environmental and economic aspects of protected crop production for four scenarios, considering in total two crops and three European locations. Interestingly, the study concluded that the highest priority, both environmental and economic, in glasshouses located in cold climates is the energy savings which can be achieved by reducing fossil fuel consumption required for heating and electricity.

As it is common in LCA studies (Cellura et al., 2012; Dias et al., 2017; Ntinas et al., 2017; Page et al., 2012; Payen et al., 2015; Torrellas et al., 2013), the analyses are based on either specific production systems or annual average production performances, and rely on energy input data obtained from questionnaires/surveys. Therefore, they serve a different purpose from the work presented in this paper. It is clear from these studies that energy requirements for the internal space heating and cooling play a significant role on their environmental assessment and potentially to the corresponding energy costs. Also, as pointed out by Torrellas et al. (2012), the most impactful elements for improvement in efficiency might differ between production systems. The present work, among other uses, can act as a tool for the simulation of glasshouse space heating/cooling processes and the development of hypothetical inputs to be used in such LCA studies. Concurrently, it can provide the ability to assess the hypothetical impact of several variables in production systems (e.g. location, technical and operational characteristics, energy sources, products) from a life cycle perspective. Also, since artificial heating in glasshouses is widely accepted in literature as a hotspot for energy consumption and global warming, this study can also act as a decision support tool for the mitigation of these impacts and improvement in performance. The present work is an extension of the work presented in Georgiou et al. (2017).

This work stands out from other studies by providing a comprehensive study focusing on the development of a tool and a case study analysis intended for the UK which incorporate the impacts of both operational and performance parameters on glasshouse energy requirements, carbon footprint and energy costs, in combination with spatial and temporal (daily and annual) variations. The present study attempts to fill this space, while quantifying and investigating the impacts of uncertainties associated with temporal weather variations. Hence, it enables the identification of influential variables that can reduce uncertainty and consequently improve the robustness and stability of the glasshouse and its stakeholders. In other words, the primary contributions of this work arise from the integration of aspects including modelling (energy, carbon, and cost), data analytics (including real weather data) and visualization, and tool development, for the creation of a generic tool with simplicity as one of the objectives.

This work is motivated by the lack of generic energy related tools focusing on the UK with limited input requirements of food growth processes in glasshouses that cumulatively consider factors such as operating conditions, design performance, varying climate patterns, geographical location and growing schedules. Such modelling frameworks can facilitate performance benchmarking and production efficiency assessment of different food producers, while also offering the identification of the most influential parameters for understanding energy performance through a parametric analysis. We can see from the aforementioned studies in literature that different studies focus on different aspects, such as design, operation, locations, time periods, production systems, KPIs, and products, which in most cases require detailed inputs. The proposed approach attempts to generalize and integrate these aspects in a simple generic tool. This tool seeks to find a balance between highly technical models and high level macro models; while still providing reasonable estimates. Therefore, this paper presents the gThermaR (Glasshouse-Thermal Requirements)
modelling framework to address this research gap.

2. Methodology

For the development of a generic tool that can be used for the purpose intended in the present study along with the capability of being applicable to a wide range of scenarios, multiple modules had to be used and integrated. This section focuses on the description of the main models, their use in the gThermA framework and their integration for the fulfilment of their purpose. Therefore, this section discusses: (i) the thermodynamic model, (ii) the spatial model, (iii) the weather data model, and (iv) the information process flow integrating the modules of the framework.

2.1. Thermodynamic model

The evaluation of energy input or output required for a glasshouse to be maintained at the required conditions is done through the quantification of the main heat loss and heat gain mechanisms. The main heat loss mechanisms are the losses due to conduction, convection and radiation in addition to sensible and latent heat losses due to infiltration. The main heat gain mechanisms are all the aforementioned ones with the addition of solar radiation. Therefore, the heat rate input and output required \( Q \) is evaluated using the following energy balance equation:

\[
Q = U \cdot A_c \cdot (T_i - T_o) + \rho \cdot N \cdot V \cdot \left( c_p \cdot (T_i - T_o) + h_{vg} \cdot (W_i - W_o) \right) - \beta \cdot \dot{V} \cdot A_r
\]

(1)

where \( U \) is the overall heat transfer coefficient, \( A_c \) is the surface area of the glasshouse cover, \( T_i \) and \( T_o \) are the internal and external temperatures respectively, \( \rho \) is the air density assumed to be constant at 1.29 kg/m\(^3\), \( N \) is the infiltration rate in s\(^{-1}\), \( V \) is the inside volume of the glasshouse, \( c_p \) is the specific heat of air assumed to be constant at 1005 kJ/kg, \( h_{vg} \) is the latent heat of vaporization of water, \( W_i \) and \( W_o \) are the humidity ratios in kg\(_{vap}\)/kg\(_{air}\) of the internal and external air respectively, \( \beta \) is the ratio of solar radiation per unit of area \( (1) \) absorbed by the glasshouse and \( A_r \) is the floor area. Similar energy balance equations have been presented in ASABE (2008), Chalabi et al. (2002), and Wass and Barrie (1984).

When \( Q \) is positive, heating is required. To convert the heat rate required into energy consumption rate as supplied by the boiler, the efficiency of the boiler \( (\eta_b) \) is considered and the result is given as thermal power. The energy can be in any form of fuel type but this will make a difference in the economic and carbon footprint of each alternative due to the variation in cost and carbon factors between energy sources. Hence, the thermal power input from the boiler \( (Q_{bo}) \) can be determined as:

\[
Q_b = \frac{1}{\eta_b} Q
\]

(2)

When \( Q \) is negative, cooling is required. Cooling in glasshouses is typically provided through natural ventilation or mechanical ventilation systems. In this model, we estimate the ventilation rate required in terms of unit of air volume extracted per unit of time to maintain the ideal internal conditions of the glasshouse. Using the energy balance shown in Eq. (1) and combining it with the impact of external air interaction through air extraction depending on the internal and external temperatures, the following expression is derived:

\[
U \cdot A_c \cdot (T_i - T_o) + \rho \cdot N \cdot V \cdot \left( c_p \cdot (T_i - T_o) + h_{vg} \cdot (W_i - W_o) \right)
- \beta \cdot \dot{V} \cdot A_r
- \frac{F \cdot A_r \cdot c_p}{\nu_i} (T_i - T_o)
\]

(3)

where \( F \) is the air flow rate through the ventilation per unit of area and \( \nu_i \) is the specific volume of the internal air. A similar approximation of cooling using ventilation is presented in ASABE (2008). In the case of mechanical ventilation, the ventilation rate required can be converted into electrical power consumption \( (E_v) \) through the use of a Specific Fan Power \( (SFP) \) variable which gives power required per unit of volume of air supplied or extracted per second as shown in Eq. (4).

\[
E_v = SFP \cdot (F \cdot A_r)
\]

(4)

Thereafter, \( Q_b \) and \( E_v \) can be converted into energy consumption by integrating over the time period \( (t) \) considered while assuming steady state conditions using:

\[
Q_b = \int_{0}^{t} Q_{bo} \, dt
\]

(5)

\[
E_v = \int_{0}^{t} E_v \, dt
\]

(6)

To estimate total energy requirements over continuous consecutive periods considering discrete time period steps \( (t_i - t_{i-1}) \) according to the data available, therefore the following expressions can be used:

\[
Q_b = \sum_{i=1}^{n} \int_{t_{i-1}}^{t_i} \dot{Q}_{bo(i)} \, dt
\]

(7)

\[
E_v = \sum_{i=1}^{n} \int_{t_{i-1}}^{t_i} \dot{E}_{v(i)} \, dt
\]

(8)

In case equal time steps \( (t_i) \) are to be considered, the average values of all variables obtained from the data sets over the corresponding time step are used and thereafter the energy requirements for both heating and cooling simply become:

\[
Q_v = \sum_{i=1}^{n} \dot{Q}_{v(i)} \cdot t_i
\]

(9)

\[
E_v = \sum_{i=1}^{n} \dot{E}_{v(i)} \cdot t_i
\]

(10)

Lastly, the quantification of the above metrics is done only during production periods depending on the growing schedules set. Different products and varieties differ in seasonality and required treatment. As a result, there are periods throughout the year in which thermal energy provision is deliberately set to zero by the model. In this way the model is able to quantify the effect of growing schedules and the difference of producing alternative products and varieties.
2.2. Spatial model

To ensure that weather data used for the model execution and evaluation of outputs is relevant, the weather station is selected following a standardized procedure based on distance proximity to the glasshouse. The distance \(D\) between two points on the surface of the earth per their coordinates is estimated based on the widely used law of cosine using the following equation:

\[
D = r \cdot \arccos (\sin \theta_1 \cdot \sin \theta_2 + \cos \theta_1 \cdot \cos \theta_2 \cdot \cos (\Delta \phi))
\]  
(11)

where \(r\) is the Earth’s radius, \(\theta_1\) and \(\theta_2\) are the geographical latitudes of the two points in radians, and \(\Delta \phi\) is the difference in geographical longitude between the two points. For a UK analysis, an additional step is incorporated to make the process easier and faster for organizations with a large portfolio of glasshouses. Given that it is common for the locations of glasshouses to be available in the form of postcodes, the tool accepts as an input the postcode of the glasshouse. Therefore, by using a UK postcode database (based on data from (Free Map Tools, 2016)) it is possible to identify the coordinates assigned to the glasshouse and the program is then executed.

Furthermore, the gThermaR model has the capability of developing maps with distinct regions based on postcode areas in the UK highlighting key metrics such as total energy use, heating and cooling requirements, carbon emissions and energy costs. Also, through the same principles, the model can quantify and map the temporal variability for all the UK regions with the goal to identify the most attractive locations in terms of both performance and robustness against external conditions. This evaluation is categorized based on postcodes registered in the UK (Free Map Tools, 2016). Each simulation’s outputs is then allocated to its corresponding postcode area polygon as formed in Opendoorlogistics Ltd (2015) (taking a sample including at least one entry per polygon). These modelling outputs are powerful and insightful features especially for organizations wanting to have an indication of which food production facilities are most attractive to partner with in terms of efficiency and sustainability.

2.3. Weather data model

The solar radiation and temperature data, acquired from the database in Met Office (2012): Met Office Integrated Data Archive System (MIDAS), are given in units that can be applied in the model after being filtered and processed. However, in the case of humidity ratio, data recorded from most weather stations are given in terms of wet bulb temperature or dew point temperature (Met Office (2012): Met Office Integrated Data Archive System (MIDAS), 2012) while some stations might have direct humidity data recorded. However, since a large pool of stations is paramount for the sourcing of weather data as close as possible to the glasshouse, the approach of dew point temperature was preferred for the calculation of the humidity ratio as defined in the energy balance Eq. (1). Thus, the humidity ratio \(W\) is calculated based on the standard methodology presented by Allen et al. (1998) in combination with the ideal gas law to give:

\[
W = \frac{e_a \cdot R_d}{R_v} \left(\frac{p}{C_0 e_a}\right)^{1/\gamma} + \frac{e_a \cdot R_d}{R_v} \left(\frac{p}{C_0 e_a}\right)^{3/\gamma}
\]  
(12)

where \(R_d\) and \(R_v\) are the gas constants for air and vapour respectively, \(p\) is the atmospheric pressure and \(e_a\) is the actual vapour pressure which can be calculated when the dew point temperature \((T_{dew})\) is available by applying the following expression:

\[
e_a = P \cdot \exp\left(\frac{A \cdot T_{dew}}{T_{dew} + 237.3}\right)
\]  
(13)

where \(T_{dew}\) is in °C, \(P\) is a constant with value 0.6108 kPa, and \(A\) is a dimensionless constant that takes the value 17.27 (Allen et al., 1998).

2.4. Information process flow

The gThermaR model process flow with its fundamental elements is presented in Fig. 1. The modelling framework comprises

![Fig. 1. gThermaR modelling framework process flow diagram.](image-url)
three main databases, three fundamental models and three main outputs that are concentrated in the section “Tool Outputs”. It is noteworthy that the model structures presented in Fig. 1 consist of their own further sub-models and algorithms, of which the highly related ones are presented in Appendix. A feedback loop has been introduced into gThermaR to allow for the execution of multiple scenarios with the overriding aim of facilitating parametric variations and analyses. Therefore, gThermaR attempts to integrate all this information through a generic tool focusing on the KPIs of energy requirements, carbon emissions and energy costs associated with protected heated production in the UK. It is worth noting all the models and simulations are executed utilizing Python programming language while in some occasions Python libraries such as Matplotlib, Pandas, TkInter and NumPy are used.

3. Results

This section includes information on: (a) the validation of the model based on a case study, (b) a parametric analysis pointing out the most influential variables in the model with respect to glasshouse’s energy performance, (c) the estimation of daily and annual energy requirements, and (d) the expected variation of energy requirements due to weather variability. Also, the impact of carbon footprint and energy costs based on different energy sources is considered. Finally, to complement and showcase the value the gThermaR tool can provide, a spatial analysis across the UK regions is performed indicating how the energy requirements change based on weather conditions.

The case study was developed in collaboration with a UK food retailer and their suppliers for which analysing the production process in strawberry farms was chosen. Activities involved visiting and interacting with strawberry suppliers with the goal of understanding their energy requirements and production schedules to deliver strawberries.

The gThermaR energy model was validated in terms of both monthly and annual heating consumption in accordance with the conditions and growing schedules specified by the strawberry farm operator. Dominant set conditions include an annual average internal temperature of 14 °C, infiltration rate of $1.5 \times 10^{-4}$ s$^{-1}$ and a growing (heating) schedule during late February until May and September until December. Fig. 2 shows the results of both analyses with respect to normalized monthly evaluations. There are some differences between the two profiles possibly due to several reasons, such as the difference in weather conditions between the location of the selected weather station by the model and the location of the farm. Nevertheless, the trend of the model follows that of the actual farm data, therefore satisfying the primary aim of this high-level simulation model.

3.1. Parametric and temporal analyses

The energy balance is affected by environmental variables such as external temperature, radiation levels and external humidity ratio. The varying conditions of these variables is subject to climatic conditions and thus cannot be controlled (other than changing the geographical location of the glasshouse). However, there are variables both in regard to internal glasshouse conditions and equipment characteristics that can have an impact on the energy requirements. Therefore, while using the methodology discussed in Section 2, a parametric analysis was conducted to observe the influence of each variable with respect to annual heat supply requirements per unit of area while holding all other variables at their nominal values. The equipment performance variables that showed the greatest influence were the overall heat transfer coefficient ($U$) and infiltration rate ($N$) over their corresponding ranges applicable ($0.57$–$6.20$ W m$^{-2}$ K$^{-1}$ and $1.40 \times 10^{-4}$–$1.10 \times 10^{-4}$ s$^{-1}$ for $U$ and $N$ respectively) based on the standard values given in ASABE (2008) (see Fig. 3(a)).

In terms of the operational variables, internal temperature was found to have a great impact on heating requirements (represented in Fig. 3(b)) even over the small temperature range considered ($12$–$16$ °C). This shows the impact on heating requirements that other products (possibly including different varieties of the same product) with different set of conditions might have if assessed. Therefore, for the climatic conditions of the glasshouse’s location and its design parameters, it is possible to quantify and analyse the impact of growing a different product. Also, temporary changes in the internal set conditions can sometimes be implemented to slightly influence yields when possible. As a result, this can potentially affect the energy requirements during those periods. A simple cost-benefit analysis of such change in production process can be carried out using the daily analysis capability of the model. This can enable assessing the energy penalty and the cost associated with this technique over the increased income obtained from the enhanced expected yield. It should be noted that this calculation is only a rough estimation given that the simulation is based on historical data from nearby weather stations. Nevertheless, a more accurate estimation should be feasible if a weather station is
available at the farm.

Since the cover’s overall heat transfer coefficient and infiltration rate were identified to be the most influential variables in the model, it is interesting quantifying their impact on energy performance in terms of both daily energy use and overall annual requirements. Therefore, a hypothetical case study of a glasshouse with a single glass sealed cover ($U$ of 6.2 W m$^{-2}$ K$^{-1}$ (ASABE, 2008)), infiltration rate of $5.6 \times 10^{-4}$ s$^{-1}$ (ASABE, 2008) and mechanical ventilation was selected as the base case. Thereafter, we studied the impact on its energy performance by changing its cover to double glass sealed with a $U$ value of 3.7 W m$^{-2}$ K$^{-1}$ (ASABE, 2008) and improving its $N$ to $2.8 \times 10^{-4}$ s$^{-1}$ (ASABE, 2008). Such analysis allows us to understand the energy reduction potential if glasshouses improve their thermal properties. Fig. 4 illustrates the results from the simulation.

From Fig. 4(a), the first thing to notice is the considerable energy reduction from the modified case. Secondly, zero values in both cooling and heating for both scenarios mainly indicating the consideration of the model in the growing schedules. Thirdly, for the base case as well as the improved scenario, there are peak demand days in both cooling and heating which are significantly greater than most of the days. However, as Fig. 4(a,b) show, through the improved case a significant reduction in terms of both the peak daily and annual demands for heating has been achieved with reductions of 47% and 57%, respectively. The same analysis was carried out for the whole UK to obtain a range of improvement of 44–50% and 51–57% for peak daily and annual demands for heating depending on the location. These reductions of course indicate an improvement in terms of efficiency of the glasshouse but they also show a more resilient system by which the external conditions have less impact on peak energy requirements. Additionally, this improvement can decrease the risk of produce quality degradation. Another issue with the peak day outliers lies in the sizing of the heating and cooling systems. The improvement in shaving these peak demands implies that heating and cooling systems can be potentially re-sized for a smaller capacity range, thus operating closer to nominal capacity and most likely at higher efficiencies (Intelligent Energy Europe, 2012). In terms of cooling while considering an $SFP$ of 0.5 kW m$^{-3}$ s$^{-1}$, the impact of these two parameters was considerably less showing a slight increase in both the annual and peak cooling requirement. Finally, the number of days requiring cooling increased by 30 while the days requiring heating proportionally decreased, hence showing a shift from heating days to cooling days. However, since the impact on heating was found to be much more influential in terms of overall energy requirements the glasshouse achieved considerably a better performance. However, one should be cautious in the modifications introduced to limit any possible negative impacts in terms of cooling requirements to a minimum. The impact of improving the energy efficiency of the glasshouse is also beneficial in terms of its
carbon footprint and the embodied carbon of the product. The magnitude of these reductions depends on the energy source as it is discussed later in this section.

A daily model simulation spanning from 1996 to 2016 for the same case study facility was conducted. Results show consistent significant reduction in annual heating requirements applying the same improvement measures proposed in the daily analysis above. The resulting reduction in mean \( \mu \) energy use was 158 kWh m\(^{-2} \) year\(^{-1} \), achieving a 56% decrease over the base case as demonstrated in Fig. 5. It is worth highlighting that a significant decrease in variance with respect to annual heating over the 21 years was noticed. The resulting decrease in standard deviation \( \sigma \) was found to be 25.4 kWh m\(^{-2} \) year\(^{-1} \). The minimization in annual variability is expected to assist in the improvement of resiliency for the glasshouse against external weather conditions as well as decreasing energy cost uncertainty. Hence, providing support for a more accurate budget forecasting for both growers and retailers. Meanwhile, the effect on cooling demand was minimal and is barely distinguishable in the graph illustrated in Fig. 6. Even though the variance and standard deviation of cooling is originally lower than that of heating, the effect of the improvement measures on these metrics was found to be negligible. Nevertheless, with the introduction of other measures, such as the improvement in SFP, it is expected to impose a greater impact and improvement on cooling loads.

3.2. Carbon and cost analysis

Beyond the energy savings (Section 3.1) that can be achieved through performance improvements, it is interesting to consider the different energy supply alternatives as these can have diverse and important impacts on the carbon and cost savings. Both mean and standard deviation calculations, with respect to annual outputs, consider a 21-year daily simulation. Figs. 7(a) and 8(a) present the carbon emissions and energy cost respectively for the two case studies considered in this work with respect to the different energy supply sources, namely natural gas, oil, biomass and electricity. Furthermore, the standard deviation of carbon emissions and energy costs for each energy source is presented (Figs. 7(b) and 8(b)).

Firstly, by observing the annual mean of the two cases, as expected there is a significant decrease in both carbon emissions and energy cost for all energy sources (for heating) considered. However, the difference between the two cases varies significantly with the change of energy sources. Interestingly, in some cases the carbon and cost savings achieved through the performance improvements to the glasshouse design is less than the saving that can be achieved through a change of energy source. For example, if we look at Fig. 7(a) and specifically the difference between biomass and natural gas or oil, the carbon savings are significantly greater by changing to biomass rather than improving the thermal envelope of the glasshouse. A similar observation can be seen on Fig. 8(a) when comparing the energy cost savings that can be achieved by changing from oil to natural gas rather than improving the glasshouse’s envelope characteristics considered in this case. Therefore, it is safe to conclude that in certain cases, especially when considering other factors such as required downtime and capital costs, it might be more beneficial in terms of carbon and/or cost to change heating fuel rather than other modifications which might give slightly higher net energy savings.

Similarly, the variability in carbon emissions and energy costs expressed in terms of standard deviation is significantly reduced, almost halved, for all heating fuels in the case of the modified scenario (see Figs. 7(b) and 8(b)). Furthermore, a considerable difference in standard deviation is also observed between the different energy sources considered, which can be greater than the difference between the base and modified cases. Consequently, the argument stated earlier in regards to the best approach towards improvement applies for variability in emissions and energy costs as well.

Attention is given to variability in terms of standard deviation in this paper to express its importance for both suppliers and retailers. There are a few reasons for this with regards to cost and emissions. For example, as in most cases in which internal spaces need to be maintained at certain conditions, weather variability can represent a great uncertainty in terms of energy requirements and corresponding costs. Therefore, a glasshouse with lower variability can be more robust and less exposed towards external conditions such as weather and climate change. As a result, greater stability in costs can result to more stable profit margins, and more accurate cost forecasting and budgeting. This is expected to be beneficial not only to suppliers but also for retailers. From the retailer’s perspective, long term partnerships with more robust and stable suppliers is preferred as seeking reliable partners is a strategic feature to build strong supply chains. Variability and uncertainty in emissions might incur an unexpected additional cost in the case of a carbon tax. However, if we assume that no additional cost is associated with emissions, the variability in emissions can still have an impact on an organization’s profile, especially when commitments for...
reduction in emissions have been made. This fact applies to suppliers as well as to retailers committed to the sustainability of their supply chains, otherwise known as Scope 3 emissions (Carbon Trust, 2017; Greenhouse Gas Protocol, 2011).

3.3. Spatial analysis

Thus far we have considered the parameters, both performance and operational parameters, that can be controlled under the gThermA framework. In this section we proceed to highlight the spatial analytical capabilities of the modelling approach. This feature is expected to have an influence on the energy requirements, emissions and costs of production due to uncontrollable parameters such as weather and landscape associated with the location of a glasshouse facility. Considering constant glasshouse design/ performance and operational characteristics equivalent to the performance of the modified glasshouse specified earlier, a daily simulation for a period of 21 years was executed for the whole UK.

The outcome of this simulation is presented in terms of heating and cooling requirements per unit of area per year (Fig. 9(a) and (b), respectively), and in terms of variability of heating and cooling requirements (Fig. 10(a) and (b), respectively). Since carbon footprint and energy costs are expected to be proportional to energy requirements, assuming the same glasshouse characteristics and energy sources, the relative distribution on the presented maps is expected to be similar.

The heating requirements are found to vary considerably

Fig. 7. (a) Carbon footprint with its associated (b) variability for different energy sources under the two scenarios analysed (carbon factors obtained from DECC and DEFRA (2016) which are used in the UK for company reporting).

Fig. 8. (a) Energy cost with its associated (b) variability for different energy sources under the two scenarios analysed (cost factors obtained from Bionordic (2011) and Bloomberg Markets (2017)).
depending on the location with the range obtained spanning from less than 100 kWh m$^{-2}$ year$^{-1}$, mostly in the southern UK, to greater than 275 kWh m$^{-2}$ year$^{-1}$ in northern areas. With regards to cooling (Fig. 9(b)), the range is much smaller than heating, spanning from around 3 to 13 kWh m$^{-2}$ year$^{-1}$, where the highest and lowest cooling requirements are distributed mostly on the southern and northern regions, respectively. Similar analyses can be made for different glasshouses with different characteristics in order to identify the most attractive location for placing them. Such insights can be very relevant when it comes to both designing new glasshouses and relocating existing glasshouses.

From the normalized maps in Fig. 10(a) and (b) we can see that the impact of the spatial parameter on annual variability is evenly distributed across the whole UK. This applies for both heating and cooling with the exception of a few regions that are either in the negative region and represent less uncertainty (e.g. some areas in the East Midlands of England), or in the high positive region that represent greater uncertainty in this case (e.g. some areas in the South West Wales). This variability can be interpreted as a level of uncertainty associated with each location. As discussed earlier with reference to Figs. 5 and 6, the minimization of this variability is desired.

Similarly, the spatial distribution of the peak daily heating and cooling requirements can be seen in Fig. 11a and b. As expected, the south of the UK shows lower peak daily heating requirements while the northern regions show requirements more than 50% higher compared to the south. Cooling is once again the reverse of the heating map, with the southern parts showing greater requirements. However, if the ranges of the two are compared, it is clear that heating is the dominant factor in the overall energy requirements. It is important to consider these peaks over several years to appropriately size the systems for periods of maximum demand. The benefit in reducing the peaks does not just lie in the ability to downsize the systems, but also in the possibility of the systems running more frequently closer to their nominal capacity and therefore potentially at higher efficiency (Intelligent Energy Europe, 2012).

The variability of the daily peaks in each year is also of interest due to its indication of the exposure of the glasshouse to extreme weather conditions resulting in excessive demands (see normalized dimensionless variability in Fig. 12a and b). In such cases, the increase in demand increases the risk that the systems installed will not be able to cope and therefore places product quality and production quotas in jeopardy.

The spatial analysis of the location of glasshouses has been found to be of high relevance when it comes to understanding energy requirements and its associated emissions and costs of such facilities. In fact, the variation that is introduced by the spatial parameter is in certain cases greater than variation observed through the change/improvement of the glasshouse characteristics. Consequently, there is a possibility of having a higher specification glasshouse performing worse than that of a lower specification one just because of their location. On the other hand, except for few areas, the uncertainty associated with the spatial parameter in terms of annual and peak daily energy requirements, emissions and costs is found to be less influential. This is in comparison to the variation of the influential parameters of the glasshouse characteristics recognized in the parametric analysis of this study: overall heat transfer coefficient of the glasshouse cover, air infiltration and boiler efficiency.

4. Discussion

A methodology for quantifying the thermal energy requirements of glasshouses applicable over a range of settings is important for careful energy assessments and performance improvements. An energy balance considering the main heat losses and gains has been proven to give reasonable estimates of the energy requirements. Internal data involving glasshouse characteristics as well as external data involving weather conditions are vital for the analysis. The combination of the different models considering energy balances, external and internal data, and the
spatial aspect, enabled the creation of gTheraR. The tool can be used for several purposes including parametric analysis, benchmarking, spatial analysis, emissions mitigation strategies and energy costs reduction strategies.

Analysis using the model has shown the energy saving potential that can exist in glasshouses by improving operational and performance variables. The parametric analysis identified the heat transfer coefficient as the most influential variable impacting heating requirements of glasshouses. This variable can be managed by carefully addressing the cover material and design of the built envelope. Furthermore, the infiltration rate which depends mostly by the age and maintenance of the glasshouse has been found to be

Fig. 10. Normalized dimensionless \( \Delta y_{\text{norm}} = (y - \bar{y})/\Delta y_{\text{max}} - \Delta y_{\text{min}} \) variability with respect to standard deviation in annual (a) heating and (b) cooling requirements.

Fig. 11. (a) Peak daily heating and (b) cooling requirements per unit area maps in the UK for the modified glasshouse based on a 21-year daily simulation.
of importance. The operational parameter of set internal temperature has also been found to greatly affect the energy requirement required for production. The improvement on performance was assessed on both peak daily and annual requirements. Improvement was observed in both metrics through the variation of both operational and performance variables. The upgrading of the cover's overall heat transfer coefficient in combination to the improvement of infiltration rate was found to significantly reduce both the annual heat supply requirement and the daily peak requirement. For the case study, these reductions were 51–57% and 44–50% respectively depending on the location. Results indicate that if heating loads are reduced there is large potential in better sizing of the heating systems in addition to providing more resilience of the system towards external conditions. The effect on cooling requirements was considerably less. Finally, the yearly variations based on analysis from 21 years of weather data showed the decrease in variability and standard deviation with respect to heating requirements through the introduction of improvement measures (see Fig. 5). Hereafter, the potential for a more stable system with less uncertainty in annual energy requirements and subsequently the provision of better cost forecasting was identified. However, the variation and impact on energy savings due to the improvement of these variables was observed to heavily depend on the location of the glasshouse.

The dynamics in energy requirements imposed by the spatial and temporal aspects have been found to substantially affect the outcome of the analysis. The impact associated with the spatial aspect of the glasshouse was studied for both peak daily and annual heating and cooling requirements. The variation observed in both metrics was substantial and therefore proving the necessity for considering the spatial factor. Also, the variation in simulation outputs while considering a longer time span was found to be affected by the location, thus indicating the combined effect of the temporal and spatial aspects (see Figs. 9–12). This is another factor to take into consideration due to the uncertainty introduced as a result of the instability in weather conditions. Even though some areas are very competitive in terms of their absolute value in heating and cooling requirements, their associated uncertainty due to the instability of the weather might make them unattractive candidates for ideal location.

Sometimes stakeholders are interested more in the costs and/or emissions of their operations instead of the energy requirements. Even though the costs and emissions are both proportional to energy consumption, their improvement can substantially vary depending on their corresponding cost/carbon factors. These factors are influenced by the energy source which can be in the form of fuel or electricity. Consequently, an improvement in energy costs and emissions can be achieved through the alteration of cost and carbon factors by exploring different energy sources as shown in Section 3.2. Interestingly, there are some cases in which the switch of energy source can have more impact than improving the operational and performance parameters of the glasshouse. Therefore, it is good practice to consider the main objective for improvement before deciding which measures to implement.

In summary, the impact of specific characteristics of glasshouses used as inputs in the model as well as external weather conditions showed to have a substantial influence on the energy requirements of the glasshouse. Thereby, indicating the importance of quantifying these variations in an energetic analysis of a food production system. Considerations to improve the performance in glasshouses include:

- improvement of thermal envelope;
- improvement of heating and cooling systems;
- alteration of internal set conditions;
- choice of products and/or varieties;
- ideal growing schedules;
- choice of location;
- change of heating fuel and electricity source.

5. Conclusions

In this paper, a first-principle modelling tool referred to as gThermaR was presented that is capable of quantifying the heating and cooling requirements of glasshouse food production. The tool was developed with the aim of helping diverse stakeholders analyse the energy requirements and sustainability metrics of this application. The gThermaR framework employs historic data from weather stations, growing schedules and requirements specific to grower and product needs (e.g. set point temperature, heating periods, etc.). It comprises multiple modules forming an integrated decision support tool. Therefore, gThermaR forms a generic tool with a range of capabilities relevant to energy requirements of protected production.

The capabilities of the gThermaR tool were tested and used to identify the most influential parameters for the energy requirements of glasshouse heated production in the UK. Both equipment performance and operational variables emerge as vital for the performance and improvement of glasshouses. Specifically, the overall heat transfer coefficient and infiltration rate were found to be the two most impactful equipment performance variables in annual heating requirements. The internal temperature was also found to play a significant role, suggesting that products more flexible to temperature exposure can present an opportunity for substantially lower energy consumption. In addition, the spatial and temporal modules of the tool revealed the importance of considering the impact of the location and time in the analysis of glasshouses. The spatial aspect showed the great variation in energy requirements between locations in the UK, while the temporal aspect showed the impact of weather variations on the uncertainty in energy consumption in heated food production. Finally, the quantified energy requirements can also be translated into emissions and energy costs by the tool. Through an investigation of a hypothetical case study based on a UK glasshouse, the potential for achieving significant emissions savings by changing the energy source to a more environmentally friendly one was also presented.

The outputs from the tool revealed the potential to address different types of problems and provide wide-ranging insight, including:

- Operational performance analysis:
  - assessing existing glasshouses in terms of their energy performance;
  - creating a portfolio of various glasshouses’ energy performances based on a standardized procedure;
  - analysing glasshouse energy requirements based on products with their associated growing schedules and required internal conditions;
  - performing cost-benefit analysis against strategies for controlling yields;
  - analysing daily energy requirements and peak demand days in a season;
  - analysing annual energy requirements;
  - forecasting the potential impact of climate variability on glasshouses’ energy requirements;
  - quantifying carbon emissions and analysis of curtailment options;
quantifying energy costs and analysis of cost reduction options.

• High-level design and long-term impact analysis:
  - analysing the geographical location’s impact on energy requirements;
  - analysing potential approaches for improvement through both independent modifications as well as through combinations;
  - inspecting expected yearly variations in energy requirements due to weather conditions and the impact of glasshouses’ modification on minimizing them.

These broad elements give stakeholders important insights that are required for comparing, benchmarking and improving energy use in food production, especially after potential commitments have been made towards ambitious environmental targets.

There are some limitations of the tool that can be addressed in future work. In particular, the tool relies heavily on weather data obtained from stations that in some cases can be located at some distance from the production site. This introduces an uncertainty in the outputs, especially for locations where there are no close weather stations. In the UK, this might not be a significant problem when substantial numbers of stations are available, however, in areas with fewer options this can introduce an additional source of error. Also, the quantifications of the tool are estimates based on a simplistic approach that can be potentially refined in future works. However, additional input requirements might increase the complexity of the approach. It would also be of interest a comparison between the outputs of the gThermaR tool and other models or approaches, and to extend the application of the model to other case studies which are expected to give different outputs.

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Appendix

The gThermaR process flow diagram presented in Fig. 1 summarizes the flow of information from the different modules of the tool. Some of these modules comprise other models/ algorithms required for their operations. The most vital ones are presented in Figs. A.1–A.3.

Specifically, the energy model process flow diagram (see Fig. A.1) shows the algorithm for using input parameters to export outputs essential for the tool’s evaluations. The spatial model process flow diagram (Fig. A.2) shows the algorithm used within the spatial model for the acquisition of the data required by the glasshouse energy model. This algorithm uses the glasshouse postcode together with the UK postcodes database and the processed weather stations database obtained from the data processing model in order to acquire each data set required by the energy model. Finally, the weather data processing model process flow diagram (see Fig. A.3) presents the algorithm used for processing and exporting the raw data in a form that can be used by the other modules of the tool.
Fig. A.1. Energy model process flow diagram.
Fig. A.2. Spatial model process flow diagram.

Fig. A.3. Weather data processing model process flow diagram.
