Demystifying Polyhouse Microclimates: A Review of Modelling Tools and Strategies

Abstract

It is impossible to feed the entire population of the world with conventional agriculture in this period of sudden climate change and degradation of natural resources. It makes it essential to adapt the protected cultivation, which makes it possible to provide favorable conditions for plant growth all-round the year. Thus, efficient management of protected cultivation techniques helps to obtain sustainable agriculture. For this, modelling of microclimate inside the greenhouse helps to better understand the dynamic variability of the microclimatic characteristics and their impact on crop growth. For this study, nearly 480 papers were reviewed on different aspects of microclimate modeling and machine learning algorithms out of which, 150 articles published in journals of high impact factors were selected and up to 80 references were cited in this article. This paper explored the available modelling techniques which include Physical-based models (offer high accuracy but require extensive computation time) and Data-driven models (faster but necessitate large datasets for analysis.). This review helps the researchers to get a detailed knowledge regarding the microclimate inside a polyhouse and various models available for greenhouse microclimate modelling and their ability to simulate the microclimate efficiently and accurately. Microclimate modeling helps understand the dynamic variations within a greenhouse and their impact on crops. The limitations of current models (computational time vs. data requirements) emphasize the need for hybrid model development. The rise of greenhouse automation and precision agriculture underscores the importance of accurate microclimate modeling. This paper, thus highlights the critical role of microclimate modeling in sustainable greenhouse agriculture, providing a comprehensive analysis of existing modeling techniques and their limitations. Thus, supporting the development of automated and data-driven greenhouse management practices.

Keywords: Protected cultivation, microclimate modeling, CFD, ML, Greenhouse automation.

1.0 Introduction

In the era of abrupt climate change, it is essential to work towards the development of sustainable agriculture. It is made possible by adapting the Protected Cultivation technique to protect the crop from adverse climatic conditions. The main purpose of protected cultivation is to create a favorable environment for the sustained growth of crop so as to realize its maximum potential even in adverse climatic conditions (Shukla *et al.* 2019, Albright *et al.* 2001). Of the various protected cultivation techniques available, greenhouse cultivation is more popular. Greenhouses are framed or inflated structures covered with transparent or translucent material large enough to grow crops under partial or full controlled environmental conditions (Gurav *et al.* 2022, Gupta *et al.* 2020, Santosh *et al.* 2017, Umesha 2011, Tiwari 2003). With this ability, greenhouse cultivation emerges as a sophisticated and sustainable method of growing plants all-round the year. The primary benefit of greenhouses is their capacity to allow farmers to actively control environmental growth factors, facilitating the year-round cultivation of various crops irrespective of outdoor weather conditions (Ihoume *et al.* 2022, Singh *et al.* 2016). The main characteristic of a greenhouse can be defined as its ability to trap the heat inside the structure due to the greenhouse effect. This helps to grow the temperate crops even in the cold regions proving that plants can be grown even in the areas that provide unfavorable conditions. The greenhouses used for growing particular crops are selected based on their type and its respective properties.

Greenhouse is classified into five types according to shape, utility, construction, covering material and cost of construction (Gurav *et al.* 2022, Akrami *et al.* 2020). All types of greenhouses influence the environment inside it both directly and indirectly. Microclimatic conditions in greenhouse are related to the characteristics of greenhouse such as size, shape, orientation, covering material, shading, cooling, heating, ventilation and influencing the crop yield and quality (Fascella *et al.* 2004).So, it is necessary to study the impact of covering material or types of protected structures on microclimate parameters and need to be determined for region specific structures the most useful (Sojithra *et al.* 2023).According to covering material they are classified as glass, plastic film and rigid panel (Sharma *et al.* 2010, Ardiansah *et al.* 2020, Gurav *et al.* 2022) and the impact of these covering materials is the most important factor to be considered when working with the greenhouses. Because, greenhouse covering material provide a controlled microclimate that may be adapted to the needs of the crops, resulting in higher yield, quality and in the lengthening of the market availability of the products (Vox *et al.* 2010, Shukla *et al.* 2019, Kim *et al.* 2022, Teitel *et al.*

2009, Papadakis *et al.* 2000). In order to provide controlled microclimate for greenhouse cultivation, it is necessary to understand the microclimate, why it should be controlled and how can it be controlled. The microclimate of a greenhouse can be defined as the environment surrounding the crop, that effects the crop physiological and morphological characteristics. The assemblage of climatological parameters forming around living plants inside a greenhouse is termed as greenhouse microclimate (Singh *et al.* 2016).

The microclimate of a greenhouse is influenced by factors such as light, temperature, humidity and carbon dioxide concentration (Santosh *et al.* 2017). In order to achieve maximum returns from greenhouse cultivation, it is important to maintain an environment that promotes optimum plant growth and production all year round (Mutwiwa*et al.* 2007). The control of microclimate can be made possible by adapting various techniques such as sensor systems, IoT, development of models and use of artificial intelligence to predict the inside environment of the greenhouse.

2.0 Greenhouse Microclimate and its control

Sustainable development of greenhouses can be achieved by efficient control and management of the greenhouse microclimate. It is because of the fact that, greenhouse microclimate that directly affects the plant metabolic activities and therefore the production (Singh *et al.* 2016). Hence, the microclimate suitable for crop growth inside greenhouses must be maintained throughout the year (Xu *et al.* 2014). The control of microclimate refers to the optimum management of temperature, relative humidity, light intensity and carbon dioxide concentration.

The greenhouse environment is a complex dynamical system characterized roughly by two main subsystems: the microclimate and the crop (López-Cruz *et al.* 2018). The crop growth inside a greenhouse structure is greatly influenced by the dynamic behavior of microclimatic characteristics prevailing inside the greenhouse. The microclimate can be adjusted according to the plants growing conditions and therefore, contribute to enhancing the quality and quantity of the crops (Sagheer *et al.* 2020). The respective adjustments of the microclimate parameters can be termed as microclimate control. The main reason for microclimate control in greenhouses is to achieve desirable plant growth and yield (Singh *et al.* 2016, Santosh *et al.* 2017). The microclimate control can be achieved in two steps. The first step in this process can be defined as understanding the crop behavior in different growth stages and the optimum conditions for the crop. The next step is to provide optimum microclimate conditions by adjusting various parameters. The micro climate conditions generated inside greenhouse can be controlled by analyzing the temperature, air velocity and humidity for optimal conditions of plant growth (Abdullahi *et al.* 2019). There exist various techniques for maintaining the microclimate parameters of temperature, relative humidity, light intensity and carbon dioxide concentration etc.

2.1 Temperature

Generally, the temperature inside a polyhouse is greater than that of the outside. This is due to the effect of greenhouse gases trapped inside the structure. Ventilation is required to allow air movement and to maintain the lowest possible temperature gradient between the outside and inside of the greenhouse (Akrami *et al.* 2020). Temperature has a direct impact on the physiological development phases (flowering, germination, development) of the plant, regulates the transpiration rate and plant water status through stomatal control during the photosynthesis (Santosh *et al.* 2017). The uniformity of plant development and crop productivity in a greenhouse is largely influenced by the dispersion of air temperature and relative humidity (Teitel *et al.* 2010). Since, the crops grown in the greenhouse are warm climate species, the temperature should be maintained around 20-30^0 C, although each crop has its own optimum temperature range. Temperature influences the air circulation, humidity levels and ventilation within the greenhouse, collectively contributing to the creation of an optimal environment for plant growth. The management of the greenhouse environment is strongly reliant on temperature manipulation (Vox *et al*. 2010). The temperature inside a greenhouse can be controlled by various techniques such as ventilation (natural and forced), shading, evaporative cooling etc. (Singh *et al.* 2018, Shamshiri *et al.* 2013). If the temperature inside the greenhouse is less than the optimum value required by the crop, the temperature can be maintained by the provision of heaters. If the temperature is high, the greenhouse can be cooled by adapting various cooling systems such as natural ventilation, fan and pad cooling system, shading and evaporative cooling. For the purpose of controlling temperature, sensors can be used to monitor the temperature and the data is analyzed using microcontroller and the actuators adapt the respective techniques to maintain the optimum temperature.

2.2 Relative humidity

Relative humidity refers to the amount of moisture present in the air compared to the maximum amount the air could hold at a specific temperature. The relative humidity inside a greenhouse varies inversely with the temperature. Temperature and RH have optimal ranges depending on the different growth stage of the plant, different greenhouse crop and different weather condition and whether it is night or day (Shamshiri et al. 2013). It is often recommended that greenhouse relative humidity be maintained in the range of 60% to 80% for healthy growth (Vox *et al.* 2010, Santosh *et al.* 2017). If the humidity is low, transpiration will be high leading to water loss and resulting in dehydration. While, if the air humidity is too high, the transpiration of the crop will be weakened and the ability to transport minerals and nutrients will also decrease (Wang et al. 2020). The reproductive processes of plants are also influenced by relative humidity. Proper humidity levels are crucial for pollen dispersal and successful pollination. Thus, maintaining RH above some minimum value helps to ensure adequate transpiration and also reduces disease problems (Gupta et al. 2020). The humidity can be monitored using sensors and can be optimized by humidification (when the humidity is lower than the optimum value) and dehumidification (when the humidity is greater than the optimum value). The relative humidity has a direct effect on the crop transpiration, leading to moisture accumulation on plants and pest attacks. Achieving and maintaining the appropriate levels of humidity is a critical aspect of greenhouse management, requiring careful monitoring and control to provide an environment conducive to healthy plant growth, disease prevention and overall crop success. The relative humidity inside the greenhouse can be maintained to desired range using ventilation during winter (reduction) and evaporative cooling during summer (increment) (Singh et al. 2018). The humidity can also be maintained by adapting the mechanized techniques of humidification and dehumidification.

2.3 Solar Intensity

Solar intensity inside a greenhouse refers to the amount of diffused light that reaches the crop after passing through the covering material of the greenhouse. Light is a key parameter which significantly affect the greenhouse crop production (Singh et al. 2018, Bersani et al. 2020). Because, light provides energy for photosynthesis and it is one of the most important conditions affecting the growth and development of the external environment crops (Imam et al. 2015). The amount of light received by the crop depends on the covering material and the solar irradiation. And, the amount of light received inside the polyhouse is always less than that of the outside environment. Thus, the choice of the greenhouses cover material is essential for optimizing crop production (Shukla et al. 2019). The light intensity inside the greenhouse was always lower (30 – 50%) than the open field (Job 2018). Optimization and control of the greenhouse light environment is key to increasing crop yield and quality (Xin *et al.* 2019). The light intensity inside a greenhouse directly effects the rate of photosynthesis, color of leaves, fruit set and fruit color. Thus, the growth and quality of crop is directly influenced by the light received. If the light intensity is too high, water loss will occur in the cells of the crop. When the light intensity is too low, the photosynthesis efficiency will decrease (Wang et al. 2020). Thus, the light intensity should be maintained at optimum levels. This can be obtained by shade nets (high light intensity) and artificial lightning techniques (low light intensity). Maintaining optimum light intensity inside a greenhouse helps to maintain the crop efficiently, since lighting plays an important role in the process of photosynthesis. Optimization and control of the greenhouse light environment is key to increasing crop yield and quality (Xin et al. 2019).

2.4 Carbon dioxide concentration

The healthiness of a crop can be justified by just having a look at it. Healthy crop has bright leaves exhibiting the abundant presence of chlorophyll. The performance of chlorophyll depends on the amount of carbon dioxide available for the plant and thus the amount of carbon dioxide present in the air directly influences the plant growth. In a controlled greenhouse setting, augmenting CO_2 levels can stimulate photosynthetic activity, leading to increased biomass production and overall growth. Carbon dioxide (CO2) accumulated over the day is an important variable which affects the plant growth in a greenhouse (Singh et al. 2018). Elevated CO_2 levels empower plants to better withstand fluctuations in environmental variables, thereby contributing to overall crop health and productivity. The net rate of photosynthesis increases with the rise of the concentration of CO_2 in a range between 0 and 1000 μmol mol^{-1} (Allen et al. 1995). The elevated amount of CO_2 results in increase in rate of photosynthesis up to a limit beyond which the elevated values have a negative impact on crop growth and quality. The production of healthy, high-yielding greenhouse crops can require the uptake of CO_2 at rates higher than the ones allowed by the typical atmospheric concentration (350–370 ppm). The enrichment of the greenhouse atmosphere with CO_2 concentrations in excess of 1,000 ppm has been found to be beneficial, with increases in growth rates and in some cases increases in product quality (Vox *et al.* 2010).

3.0 Modelling and Prediction of Greenhouse Microclimate

The greenhouse production agro-system is a very complex process, where physical, chemical and biological processes take place at the same time with different patterns and time scales. For that reason, model-based tools are required as support to understand the dynamics of these system (Munoz *et al.* 2020). Greenhouse microclimate modelling represents an advanced approach within agricultural science and engineering, aimed at understanding and manipulating the environmental conditions within a greenhouse setting. It is a difficult task mainly due to the strong nonlinearity of the phenomenon and the uncertainty of the involved physical and non-physical parameters (Guesbaya *et al.* 2022). By considering variables like temperature, humidity, radiation, and airflow, these models offer valuable insights into how these elements interact and impact plant growth. The greenhouse environment is a very complex dynamic system covered with thin and transparent materials (Mohammadi *et al.* 2018). Thus, a dynamic analysis is required for more accurate prediction and control of greenhouse thermal environments (Yildiz and Stombaugh 2006). Simulation models to describe the dynamic behavior of the air temperature, humidity and carbon dioxide concentration inside the greenhouses have been published in several studies. Modelling the microclimate of a greenhouse differs depending on the purpose. There are two main categories of models, the physical based, which are mainly used if the main purpose is the study and knowledge of the natural processes that take place within the greenhouse and the black-box models, if the main objective is the applications and design of systems related to greenhouse management (Petrakis *et al.* 2022). Cunha (2003) categorized the greenhouse microclimate models as: Physical based models, Black box linear parametric models and Black box non-linear parametric models. Dynamic models are built to augment our knowledge of systems in general and to enhance the understanding on the dynamics of the greenhouse environment (López-Cruz *et al.* 2018). The main objective of greenhouse microclimate modelling is to quantitatively describe the energy and mass transport processes by mechanism of convection within the medium, the exchange processes between air and plant elements and other surfaces, and the ways in which plants respond to the environmental factors (Singh *et al.* 2016).

From the studies, it was observed that the 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).

S.no.	Theme of articles	Parameter	No. of authors studied/used	Key findings
1.	Greenhouse microclimate	Monitoring and control of microclimate	45	Monitoring data provides valuable insights into the greenhouse environment. Continuous monitoring of temperature, humidity, light intensity, and CO2 concentration allows for early detection of deviations from optimal levels. Maintaining an optimal microclimate leads to healthier plants with higher yields and better-quality produce
		Effect of microclimate on the crop	15	Microclimate has a profound effect on all stages of crop growth, from germination to yield. Temperature and humidity play a critical role in seed germination. Light intensity, temperature, and CO2 concentration all influence vegetative growth. Day length, temperature fluctuations, and light intensity can significantly affect flowering and fruit set.
		Greenhouse microclimate models	58	Greenhouse microclimate models are crucial for simulating and predicting temperature, humidity, light intensity, and CO_2 concentration within a greenhouse. They can be used to develop control strategies for these systems to maintain desired microclimate conditions. They offer insights into microclimate dynamics, facilitate the design of optimal growing conditions.
2.	CFD (Computational Fluid Dynamics)	Greenhouse microclimate (Temperature, Relative Humidity, Light Intensity and Carbon dioxide Concentration)	66	CFD allows to understand the complex interactions between temperature, humidity, light, and CO_2, leading to the design of greenhouses with ideal growing conditions for various crops. The dynamic variability of the microclimatic parameters is analyzed and necessary strategies to be adapted for efficient control of these parameters is discussed. CFD simulations can predict humidity variations and temperature fluctuations in the greenhouse.
		Ventilation and Vent configuration	88	Through CFD simulations, it is possible to analyze the impact of vent size, location, and type (e.g., roof vent, side vent) on airflow patterns. CFD can analyze airflow patterns within a greenhouse down to a very detailed level, considering factors like wind speed, direction, and turbulence. This leads to improved ventilation efficiency, reduced energy consumption, and ultimately, a better growing environment for crops.
3.	Machine learning	Microclimate prediction and control	129	Machine learning models are highly effective tools for greenhouse microclimate prediction and control. These are strong contenders, achieving high accuracy in predicting temperature, humidity, and CO_2 levels. ANNs excel at short-term forecasts and can achieve very high accuracy with minimal error.
4.	AI and IOT	Cloud based platforms for precision control of microclimate	50	Cloud platforms enable real-time monitoring and adjustments to microclimate, leading to optimal conditions for plant growth, potentially increasing yield and improving crop quality. They allow growers to monitor and control their greenhouse environment remotely, improving accessibility and flexibility in managing microclimate.
		Greenhouse automation	28	Automated control of temperature, humidity, irrigation, and ventilation creates optimal conditions for plant growth, leading to higher yields. Automated systems collect and store data, enabling growers to analyze trends and make informed decisions about resource allocation and crop management

Table .1: Key Findings of reviewed articles

3.1 Physical- Based Models:

Physical-based modelling of microclimates is a comprehensive approach that draws upon principles from physics, meteorology and environmental science to simulate the intricate interactions between environmental factors within localized areas. Physical based models are developed based on the physical processes taking place inside a greenhouse which includes the heat exchange and energy exchange processes. At the core of physical-based modelling of microclimates lies a comprehensive understanding of atmospheric dynamics, which encompasses the movement of air masses, temperature gradients and wind patterns. The development of a physical model presents a high degree of difficulty, especially because the greenhouse is a nonlinear complex and it is mainly based on the laws of thermodynamics and of heat transfer and mass transfer (Petrakis *et al.* 2022). Physical modelling of greenhouse climate started already in the seventies, but information available is not sufficient enough (Bot 1991). Bot (1988) constructed a physical-based model from the sub-models representing the heat and mass transfer processes and these sub-models were validated and then the final model was verified. In conclusion, physical-based modelling of microclimates represents a sophisticated approach to understanding and predicting the complex interactions between environmental factors within localized areas. By integrating principles from physics, meteorology and environmental science, these models provide valuable insights into the spatiotemporal dynamics of microclimates and their implications for various applications, ranging from agriculture and urban planning to environmental management and climate change adaptation.

Physical-based models are also known as Process-based models, since the core of the model lies in representing the energy balance processes. Greenhouse microclimate modelling using Computational Fluid Dynamics can be characterized as Process-based model. The study of microclimate distribution in greenhouse structures in recent years is mainly addressed through CFD simulation approaches and from dynamic mass and energy balance models (López-Cruz et al. 2018). CFD, which is considerably more complex and computationally intensive, allows to describe heterogenous attributes of the greenhouse air and their change through space and time (Katzin et al. 2022). CFD (computational fluid dynamics) has been used to replicate greenhouse conditions and study the effect of ventilation arrangements, air velocities and other parameters on the conditions inside the greenhouse (Akrami et al. 2020). In particular, three-dimensional CFD analyses have been successfully used to predict and improve the air profiles surrounding the growing crops (Zhang et al. 2016).

Numerical analysis based on computational fluid dynamics (CFD) can predict and analyze the airflow characteristics of the model that are difficult to be analyzed by experiments (Yun 2002).The CFD technology has been shown to be an effective and mature tool to be used in controlled environment agriculture for analyzing aerodynamics, climate and complex fluid phenomena (Baeza *et al*. 2009; Bournet *et al.* 2007; Fatnassi *et al.* 2015; Fidaros *et al.* 2010; Lee & Short 2000; Majdoubi *et al.* 2009; Tamimi *et al.* 2013). Thus, CFD has been studied by many researchers in various aspects.

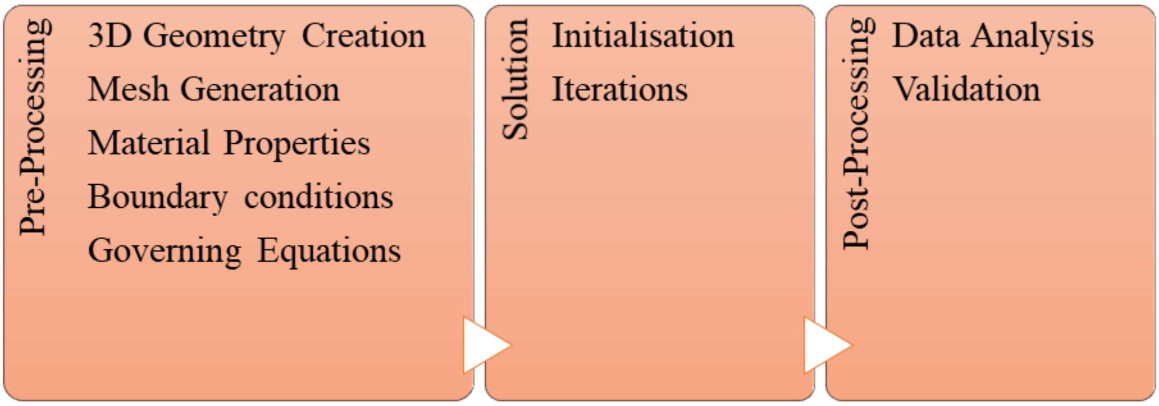

Figure 3.1: Flow Chart representing the work flow of a CFD model

Computational fluid dynamics (CFD) has been used as a powerful tool by various researchers to investigate distributed climate heterogeneities inside a greenhouse and in particular inside a crop (Kichah *et al.* 2012),simulating physically complex phenomena and the distribution of climate parameters(Tamimi *et al.* 2013), to simulate the climate inside greenhouses (Bournet 2014),to evaluate the efficacy of the ventilation strategies and for analyzing the flow within plant factories or greenhouses (Plas *et al.* 2023), to analyze the airflow pattern on the crop canopy under different ventilation modes in a single cultivation bed (Fang *et al.* 2020),to model the climate generated inside the greenhouses and for the development of structural design improvement with regard to ventilation effectiveness (Molina-Aiz et al. 2004), to study the air flow distribution in a high-pressure plant growth system (Peiro *et al.* 2020), to simulate evaporation and condensation processes that occur in hemispherical solar stills (Panchal and Shah 2013).

The specificity of CFD is to allow the calculation of variable fields at a set of discrete points in the calculation domain through the resolution of the corresponding transport equations (Bournet 2014).The way the boundary conditions are identified and included inside the CFD model plays a crucial role in the quality of the numerical results (Kichah *et al.* 2012).Computational fluid dynamics (CFD) has been shown to be an effective tool in simulating physical complex phenomena with reasonable accuracy and analyzing environmental uniformity in controlled environments (Zhang *et al.* 2016).Through the advancement of software, CFD modeling has seen a tremendous amount of improvement recently, enabling microclimate research to better comprehend the relationships between climate variables inside greenhouses. CFD simulation has improved in realism and detail over the past few years, leading to more precise results (El Alaoui *et al.* 2023).

3.2 Computational Models:

Computational models (Black-Box Models) are defined as the mathematical models that uses mathematical equations to describe the dynamic behavior of microclimate inside a greenhouse structure. Black-box models are based on the system identification (SI) process. SI is a methodology that depends mainly on experimental input and output data. These models provide an effective and accurate description of the behavior of various parameters without the need to model the internal system processes (Zhang *et al.* 2010). 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 (Katzin *et al.* 2022).

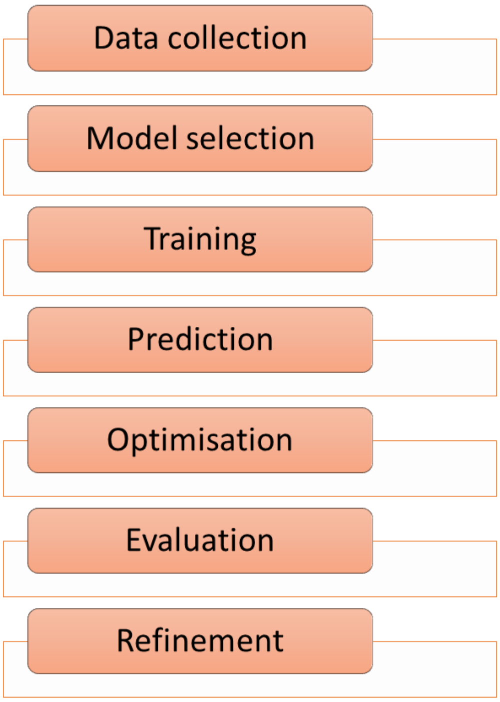

Figure 3.2: Flow Chart representing the work flow of a Machine Learning model

Data driven models refers to the application of Machine learning models and Artificial Neural Networks that use data as the main input to model and predict the greenhouse microclimate. Machine learning describes the capacity of systems to learn from problem-specific training data to automate the process of analytical model building and solve associated tasks (Janiesch *et al.* 2021).These models analyze the available historical data to predict patterns and behavior of dynamic variability of the microclimate.ML means that a computer program's performance improves with experience with respect to some class of tasks and performance measures (Jordan and Mitchell 2015).Machine Learning (ML) techniques have proven robust, reliable, and efficient in dealing with sparse and multivariate climate datasets (Wang *et al*. 2016). Data driven/machine learning technique-based approaches have also been applied for greenhouse crop yield forecasting in many studies, which treat the crop yield output as a very complex and nonlinear function of the greenhouse environmental variables and historical crop yield information (Gong *et al.* 2021). An Artificial neural network (ANN) simulates human brain in establishing relationships between inputs and outputs. It constructs its knowledge background from historical data (El Alaoui *et al.* 2023). One of the primary advantages of ANNs is their capability to predict based on patterns and relationships in input factors, with a wide range of applications, including image and speech recognition (Nugroho *et al.* 2019, Wahyuni *et al.* 2017) and hydrological and environmental forecasting (Humphrey *et al.* 2016, Wang *et al.* 2015).A neural network initially captures how the internal climate properties and sensor signals interact, which is then shown linguistically via an algorithm based on fuzzy logic (Lachouri *et al.* 2022). Advanced non-linear techniques like ANNs or machine learning algorithms are often explored to model complex systems. These techniques are designed to capture non-linear dynamics that may exist in the data, leading to more reliable and accurate results than linear techniques in many cases (Sun *et al.* 2023). Accurate prediction models for greenhouse and plant growth performance can be used as a design tool and in economic feasibility analyses as well (Yildiz and Stombaugh 2006).

Since, greenhouses are complex and non-linear systems (Escamilla-García *et al.* 2020), an efficient climate-based management for these systems require algorithms that can autonomously learn the underlying patterns within the collected data then map them to the most optimized control actions (Ihoume *et al.* 2022). It leads a path for combining the process- based and data driven models. With the rapid development of computing power and higher data availability, developing hybrid frameworks that combine physics-based and data-driven approaches is becoming increasingly popular among researchers (Javanroodi *et al.* 2022).

4.0 Emerging technologies:

Greenhouse monitoring and automation are currently one of the most discussed subjects in the agriculture sector (Ardiansah *et al.* 2020). The purpose of an automatic greenhouse is to ensure that the plant needs are covered in an efficient and accurate way (Achouak *et al.* 2018). Smart greenhouse farming is an emerging indoor farming that refers to managing the greenhouse using information and communication technologies (ICT) to increase the crops' quantity and quality while optimizing the human labor required (Kodali *et al.* 2016, Dan *et al.* 2015, Bersani *et al.* 2020). In this regard, wireless sensors and remote monitoring-and-control instrumentation that benefits from the concept of the Internet-of- Things (IoT) have been deployed in smart farming to help growers stay updated (Hemming *et al.* 2019, Tzounis *et al.* 2017). Modern high-tech greenhouses feature an array of standard sensors for monitoring light, temperature, humidity, and CO_2 levels. These are complemented by various actuators for active control, including lighting, screening, heating, ventilation, cooling, CO_2 dosing, fogging, dehumidification, irrigation, and fertilizer dosing. This comprehensive control allows for meticulous management of all critical growth factors essential for optimal crop production at any given moment (Hemming et al. 2020).

This review of numerous studies on greenhouse microclimate control and modeling techniques reveals a key insight, that efficient microclimate optimization can significantly enhance greenhouse productivity. While modeling techniques (ML and CFD) have limitations, they offer valuable tools for maintaining ideal growing conditions. The optimal modeling approach depends on several factors, study purpose, greenhouse type, data availability, time constraints, accuracy requirements and financial resources.

Choosing between CFD and machine learning models for greenhouse microclimate management involves a trade-off between accuracy and efficiency. CFD models offer unparalleled detail and physical accuracy. They can simulate complex interactions between airflow, heat transfer and plant growth, allowing for highly precise predictions of microclimate variations within the greenhouse. CFD simulations require significant computational power and expertise to set up and interpret.

Machine learning models, on the other hand, excel at processing large datasets and identifying patterns. They can learn from historical sensor readings to predict microclimate changes and recommend adjustments to control systems. This translates to faster analysis and potentially lower implementation costs. However, the accuracy of machine learning models depends heavily on the quality and quantity of training data.

In the end, there's no single "best" model. The optimal choice depends on the specific needs and resources available. CFD offers superior accuracy for in-depth analysis, while machine learning provides a faster and potentially more cost-effective approach for control optimization. Hence, it can be said that both the models are equally potential in their own way of processing. As research progresses, hybrid models that combine the strengths of both techniques might emerge as the future of greenhouse microclimate management.

5.0 Conclusion:

The most practical protected cultivation method to accomplish the goal of sustainable production is the use of Greenhouses. It is important to study the dynamic behavior of the greenhouse microclimate for effective optimization to enhance the crop productivity. This can be done by using model-based techniques. In this paper, different modelling techniques for greenhouse microclimate modelling were presented. The models were primarily classified as Physical- based models and Data driven models. Numerous researchers used CFD and Machine learning models for the modelling of greenhouse microclimate. The findings of various studies represent that CFD offers unparalleled physical accuracy for in-depth analysis, while machine learning provides a faster and potentially more cost-effective solution for control optimization, while describing the disadvantages of these models as heavy computational requirements and requirement of large spatio-temporal data respectively. Hence, it is evident that no single modeling approach is a silver bullet, each model having its own merits and limitations, can be employed based on the requirement of the study. Currently, many studies were focused on development of hybrid models. By embracing these advancements in modeling tools and strategies, growers can optimize their polyhouse microclimates for sustainable and efficient crop production.

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