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An Overview of Different Fruit Crop Models in the last 40 Years to Date with Their Main Uses

Amina Shukoor [a++], Shikha Jain [a++*], Poonam Maurya [a++], Laya P. [a#], Chukamettu Anusha [a++], Anagha P. K. [a++], Amulya S. [a++], Akhila B. S. [b++], Bhargav Kiran [c++] and Kiran Kothiyal [d†]

[a] Division of Fruits and Horticultural Technology, ICAR- Indian Agricultural Research Institute, New Delhi- 110012, India.
[b] Department of Fruit Science, College of Agriculture, Vellayani, Kerala Agriculture University, India.
[c] Division of Vegetable Science, ICAR- Indian Agricultural Research Institute, New Delhi-110012, India.
[d] Department of Horticulture (Fruit Science), Govind Ballabh Pant University of Agriculture and Technology Pantnagar, Uttarakhand-263153, India.

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Horticulture is a versatile field which encompasses a plethora of day to day strategic decisions like varietal selection, optimisation of resources, understanding the mechanisms of the phenology, identification of plant invaders both in the micro and macro level, wise and judicious use of plant

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[++] Ph. D. Research Scholar;
[#] M. Sc. Fruit science;
[†] M. Sc. Ag.;
**Corresponding author: E-mail: jain64235@gmail.com;*

protectants, yield prediction & assessment, post harvesting & handling, strategic way of understanding the pulse of consumer's popular demands and efficient way of marketing. Fruit trees are perennial unlike annual vegetable and cereal crops where there is a high prerequisite for efficient modelling of canopy architecture, photosynthesis, nutrient uptake, pest forecasting etc where the ill-effects of climate change are bringing out huge losses in the existing germplasm, annual turnover of the farmers and emergence of unheard pests and diseases. An invincible foresight or preparedness against such vagaries can be brought out by efficient modelling mechanisms combining the physiology, phenology and vital requirements of fruit trees with the interacting ecosystem of the land where it is present. Extrapolating such models from the local level to a general situations always gives fruitful results and it further aids in strengthening the present protocols. With the advancement of machine learning and deep learning in precision agriculture, problems of farmers and orchardists are being solved at a faster pace with the help of sensors in identification of problems and its alleviation using fast and error-free processing at pre-harvesting, harvesting and post-harvesting stages of fruit crops. In fact it is also one of the major concerns among people regarding the complete replacement of human power in the crucial decision support systems for agriculture and farming.

Keywords: Modelling; phenology; machine learning; deep learning.

1. INTRODUCTION

A good decision support system is based on contemplating on the real picture of the situation and formulating procedures or solutions to bring it under control. [1] defined a model as the "schematic representation of the system". As we are in an era witnessing the brunt of catastrophic climate change, the use of crop modelling will definitely help in saving our crops from the dreadful effects of biotic and abiotic stresses to a great extent with a scientific conviction of practical actions and futuristic vision. During the last two decades, horticulture has also developed in the area of crop modelling. Like in every field, some of the concepts, tools, approaches and bottlenecks are also applicable in this field. Plenty of information has been contributed to the horticulture community in the field of crop modelling by three working groups of International Society for Horticultural science (ISHS) namely, the 'Modelling plant growth, environmental control and green house environment' group, the 'computer modelling in fruit research and orchard management' group and the 'Timing field production of vegetables' group [2][3] opined that it may be anticipated that a branch of science will reach the stage where the linkages between theory and experiment are most effectively made by using the language of mathematics as it moves from the qualitative to the quantitative. USDA in the year 2007 defined crop models as computer programmes that simulate how crops grow and develop.

Tree modelling is a thorough revision of crop phenology linked to changing climatic conditions and it uses a variety of models, such as phenological models of diverse plant systems, water models, nutrition and nitrogen dynamic models etc to predict the specific behaviour of plants in a changing climate [4]. The majority of horticultural plants have discontinuous canopies, which have complicated effects on gas exchange, light interception, and aerodynamics and because of these problems, coupled techniques that combine crop physiology and micrometeorology have been justified [5], [6]. Studies by [7] reported on the impact of rising global temperature on stone fruits and thereby stressing the significance of lowering the winter chilling requirements and shifting the areas of production explicitly. Crop modelling is also a very useful tactic which can be used at the operational level to stimulate some of the short term processes such as CO_2 and water vapour exchange that interact with the green house climate, thereby maintaining the day-day carbon accumulation in the plant which further helps in the crop growth [8] as shown in Fig. 1.

Models are the most used teaching aids for communicating horticultural principles to the students. A simulation model of the carbon supply and demand for reproductive and vegetative growth in peach trees (PEACH) was developed using the premise that carbohydrate partitioning is controlled by competition among individual plant organs, based on each organ's growth potential. Scientists get a lot of benefits from crop modelling in prioritising research areas and understanding the importance of certain parameters involved in the interactions in soil-plant-atmosphere system [9]. Crop models based on phenology, epidemiology and insect control helps in taking strategic management decisions and optimisation of resources with accurate predictions and warning systems. The introduction of machine learning models and artificial intelligence technology helps in flawless predictions from unseen data sets and leads to smart decision support systems. Now a days protected cultivation techniques and post-harvest industries automated with high resolution sensor technologies avoids the perils of human error and brings out maximum productive results. The main objective of this review is to narrow down the technological gap between the conventional and modern technologies in the area of crop modelling in horticulture crops and to know the ways in enhancing decision support systems with the use of such models on a timely basis so as to bring fruitful results throughout the production cycle of fruit crops.

2. CLASSIFICATION OF MODELS

Models can be classified in to conceptual, mathematical and physical [10]. Conceptual models are centred on a hypothesis from a deep thought or scientific imaginations. Physical models are experimental subsystem unit representing a whole system and are not involved in the explanation of biological systems. Mathematical models are the most widely used one where the behaviour of the system is described mathematically through equations and assumption of hypothesis is done quantitatively with deduction of its consequences. Different classes are there within the mathematical models of which empirical models and mechanistic models are most important. Both empirical and mechanistic models can be deterministic which includes the use of definite quantitative predictions or stochastic which uses random predictions and have a range of distributions [11]. They can either be continuous or discrete. Simulation models and optimisation models depends on mathematical modelling.

2.1. Empirical Models

It includes direct descriptions of observed data without any scientific content which are usually expressed as regression equations and are used to obtain the final data. Regression equation is based on one or a few factors. This model is used to study the effect of fertilizer application with the crop yield, relationship between leaf area and leaf size in a given plant species [12]. The mechanisms behind the processes which gives rise to response isn't studied here.

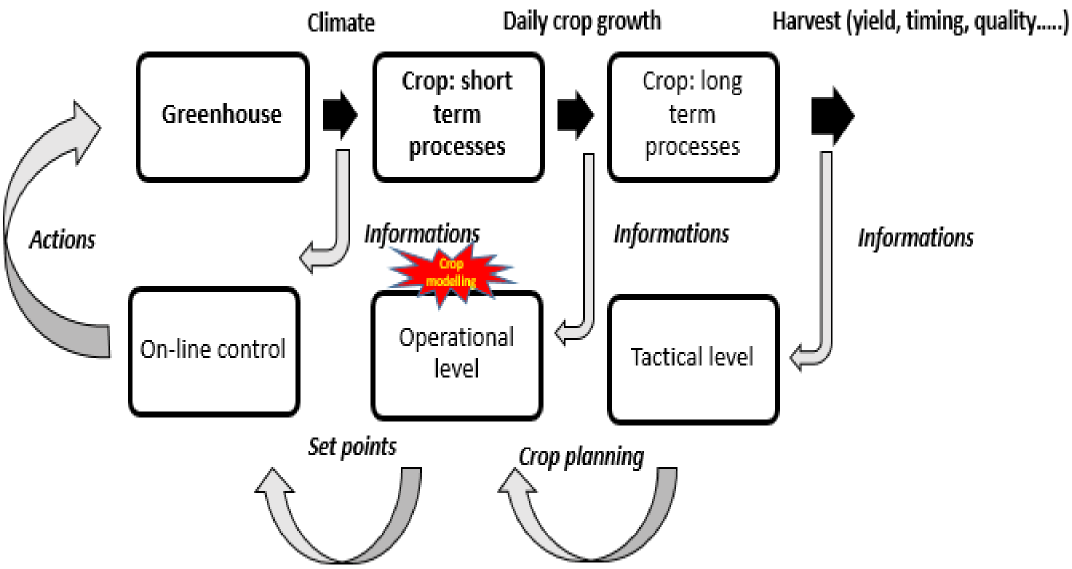

Fig 1. Representation of an organised structure for managing greenhouse climate and crop. On-line control sets point tracking and transfer of informations and conveying actions, crop modelling represents the operational level which stimulates transient factors interacting with the green house climate. Tactical level uses models needed to link the comprehensive approach of crop management throughout the crop cycle and climate control to yield formation [8]

2.2. Mechanistic Models

A mechanistic model is one that breaks down a system's behaviour into its lower-level properties. The lowest levels therefore have a mechanism, understanding, or explanation (such as cell division). This model has the ability to resemble important physical, chemical or biological processes and also describes how and why a particular response occurs [12]. This model explains the relationships of dependent variables influencing a process. The first mechanistic model was that of processed-based models focusing on photosynthesis, respiration, transpiration and its influence on the growth of the plant and here plant growth is modelled as a process dependent on environmental conditions such as light, temperature, and CO_2 concentrations [13], [14]. Some of the processed-based models are given in Table 1.

2.3. Deterministic Model

A deterministic model makes accurate predictions for quantities for eg: rainfall or crop yield without any probability distribution, variance etc. In some cases it brings unsatisfactory results e.g. in rainfall prediction. The more uncertain the system, the less useful deterministic models are.

2.4. Stochastic Models

According to [22], different outputs are provided along with probability for each combination of fixed inputs. It is advisable to create a stochastic model that provides an expected mean value as well as the related variance when variation and uncertainty are at a high level. Whenever proper results aren't obtained from an experiment, it is advisable to use stochastic models.

2.5. Simulation Models

This model is designed for the purpose of replicating a system's behaviour. Computer models that represent a system in the actual world are used in simulation models with mathematical representation. Estimating agricultural productivity as a function of weather, soil, and crop management is one of the fundamental objectives of crop simulation models. It requires a large amount of input datas and satisfactory management strategies for the model to function properly at a lower cost. Simulation models are designed to provide dynamic, quantitative and frequently visual solutions to scientific concerns [23]. The other advantages of simulation models include climatically-determine the yield in various crops, scoping best management practices under a given cropping system, to study the potential climate change projections, improvement in the experiment documentation and data organisation and breeding new crop varieties by understanding the genotype × environment interactions.

2.6. Static and Dynamic Model

With relation to the time, static model describes static objects which doesn't get changed with the influence of time and dynamic model, when the state of the object changes according to the time.

2.7. Optimising Models

This model serves the purpose of finding out the best option in terms of management inputs for the successful operations of the system. Some important set of instructions are adopted which can fit best with the intriguing problem.

2.8. Functional- Structural Plant Models (FSPM)

This model can determine the 3D architecture of the plant influenced by the natural physiological processes which are affected by environmental factors. It can combine structural information with physiological functions making it as a useful tool in describing the realistic growth and the development of the crops [24]. Different modelling strategies have been utilised in different models with different elementary units [25], [26]. The different elementary units are "metamer/phytomer" which consist of node with axillary leaf, axillary buds and an internode [25], "growth unit", a part of an axis that is formed as a result of non-stop elongation [27], "axis" which is a sequence of units of growth in same general direction from one (monopodial) or more (sympodial) meristems [26] and "branching system" which is an organisation of branches within the same plant [28]. Different formalisms have been proposed for the developmental processes, of which language based using L-system grammar [29] is most commonly used one. An insight in to the source-sink relation is also obtained from FSPMs such as L-peach [30], L-Kiwi [31] and Lignum [32]. The GreenLab model is a stochastic and discrete mathematical functional structural plant model which make use of the conjunction of functional and structural descriptions for physiological processes with the elemental repeats like “phytomer” [33]. FSPM takes in to account other components such as photosynthesis, respiration, nutrient uptake and light interception besides canopy structure & architecture and root system of the trees.

2.8.1 Structure and architecture of perennial fruit trees

The fundamental elements of tree development are identified by the architectural models of trees. A few fundamental ideas, including axis types with monopodial or sympodial ramifications and axial or terminal flowering are the foundation of architectural forms and their repetitions. Today it is commonly acknowledged thatwith the structure of plants is the consequence of a succession of elemental repeats like “metamer” /“phytomer” (a structure comprising an internode which ends in a node on which organs such as leaves, fruits and axillary meristems are attached), “axis” (represents meristem’s functioning), “branching process” prevailing in a tree and finally the “growth unit” (a part of an axis formed as a result of nonstop elongation). The different examples of models with the corresponding species and its elemental repeats are given in Table 2.

Table 1. List of some processed-based model along with the corresponding species and the process which it deals with along with references

Name of the model	Species	Processes it related with	References
-	*Actinidiadeliciosa*	Acquisition of carbon and its utilization, hydrolysis and restoration of carbon reserves and maintenance of perennial biomass	[15]
PEACH	*Prunuspersica*	Carbohydrate partitioning, growth, photosynthesis, respiration, carbon supply & demand	[16]
ALMOND	*Prunusdulcis*	Carbohydrate partitioning, growth, photosynthesis, respiration, carbon supply & demand	[17]
QualiTree	*Prunuspersica*	Horticultural practices: (thinning, pruning and irrigation) influence fruit quality and growth	[18]
VitiSim	*Vitisvinifera*	Carbon partitioning and carbon balance, respiration of organs and daily photosynthetic rate	[19]
OliveCan	*Oleaeuropaea*	Water balance: root water uptake, soil evaporation, drainage and precipitation Carbon balance: partitioning of assimilates, maintenance and growth and respiration	[20]
MaluSim	*Malus× domestica*	Fixed carbon, respiratory costs, carbon exchange among the plants, effect of environmental changes and cultural practices on dry matter	[21]

Table 2. List of models along with the corresponding crops using different elemental repeats and its reference

Name of the model	Crop scientific name	Elemental repeats	Reference
LIGNUM	*Pinussylvestris* L.	Growth unit	[34]
INCA	*Juglansregia*	Growth unit	[35]
L- KIWI	*Actinidiadeliciosa*	metamer	[36]

2.8.2 Canopy architecture of perennial fruit trees

[27] reported some models based on canopy architecture and called as architectural/geometrical models. Plant architecture description is based on three types of information: composition, geometry and topology [37], [38]. The definition of the three types of information given by the authors are given below:

Composition: Different types of elements which composes the plant constitutes its composition. Plant architecture is described from simplest to most detailed by some representations like globular, modular and multi-scale [38]. In globular representations, plants are considered as whole. Some of the geometric figures like ellipses and cylinders are used to describe the trunk and canopy of the plants. In modular approach, plant is described by selecting any of the repeating units that composes the plant i.e. metamers, growth units and axis [39]. Multiscale representation is based on objects that can be described at every scale [40], which can completely describes the complexity of plant architecture. The multi-scale tree graph (MTG) is the result of several tree graphs, each one at different scale.

Geometry: shape and spatial position of components like leaves, fruits, internodes or different types of growth units. The spatial distribution of leaves can be associated with the light interception and arrangement of roots and its ramifications predict its uptake efficiency to nutrients and water present in the soil. Geometrical representations always provides a detailed perception about the interaction of plants with its micro-environment [41], [42], [43].

Topology: characterizes the connection between the elements. They can be described by using specific formalisms such as Lindenmayer-system or L-system. In L systems, a module is defined as repeated plant units such as metamer, apex and branch. It mainly consists of a set ofrewriting rules. Problems with carbon partitioning are also addressed using plant topology [38]. Pipe model theory is used to simulate the thickness of stimulated stems and roots as well as xylem and phloem conduits [44], [45]. According to the "pipe model theory," the total cross sectional area of stems and branches at a given height is proportionate to the total number of leaves present above that height [46]. By joining together unit pipes that represent plant parts, complex branching systems can be modelled. With the aid of magnetic or sonic digitizers [47], [48], allometric relationships [49], [50] or by the use of photographs [51] plant topology can be evaluated.

2.8.3 Aerial parts of perennial fruit trees

According to [52], it is very important to study the types of shoots (long/ short shoots/ shoots with already formed/ newly formed organs and diameter), organ development and form (phyllotaxy, shape, orientation and size), types of branches (monopodial/sympodial) and form of the tree (cone/globular). A Markov process is a stochastic process that satisfies the Markov property, also known as "memorylessness," which essentially states that one can predict a process's future based only on its current state, i.e., the system's present state determines both its future and past states [53]. For assessing the branching patterns along the trunks of various apple cultivars, local-scale empirical models were created [54]. Markov models were used to observe and empirically describe a sequence of separate homogenous zones along the trunk [55]. These Markov models were also used to analyse the zones seen in peach tree shoots of various lengths [56]. Markov models and semi-Markov models are used to statistically assess the transitional probability between two zones [57]. Some of the examples in which Markov's models and semi- markov's is applied in fruit crops are GrapevineXL in grapevine [58], L-ALMOND in almond [59], [60], L-KIWI in Kiwi [61], L-PEACH in peach [30] and MappleT in Apple [62].

2.8.4 Root system of perennial fruit trees

To accurately depict the functioning of the entire plant, root apparatus modelling is essential [63], [64]. Since the root system is underground, mapping root architecture is more challenging than mapping the canopy since invasive and destructive approaches are required to investigate it [65]. In FSPMs roots are poorly represented and they are collectively considered as single module only and in herbaceous crops, it is widely dealt with considering each and every aspects of root system. In perennial fruit crops, there are some complexities like the root mortality of fine roots and structural roots. Some of the root apparatus modelling used in fruit crops are given in Table 4.

Table 3. List of root apparatus modelling used in the fruit crops along with its purpose and references

Crop	FSPM Model name	Purpose	References
Walnut	INCA	Root system is described very simply by three compartments: (taproot, coarse root and fine root)	[35]
Walnut	SIMWAL (SIMulatedWALnut)	Root system is described very simply by three compartments: (taproot, coarse root and fine root)	[66]
Plum	-	Dynamic 3D representation of the root system architecture of plum including two information levels (i) typology of root axes and (ii) a set of basic processes like axial & radial growth, ramification & reiteration and decay	[67]
Kiwi	L-KIWI	Root growth is modelled considering only the fibrous roots	[31],[45]
Almond	drainage lysimetermodel	Emperical experiments regarding the effect of nutrients	[68]

Table 4. List of models focusing on light interception in tree canopies with its purposes and the approach it is based on along with references are given below

FSPM Model name	Purpose	Approach which it is based on	References
The nested radiosity model	Modelling of distribution of natural light	Turbid medium approach (Monsi and Saeki 1953)	[41]
RATP	Simulates the spatial distribution of radiation absorption, transpiration and photosynthesis inside the canopy	Turbid medium approach (Monsi and Saeki 1953)	[71]
Quali Tree model	Computation of photosynthetic active radiation (PAR) considering the canopy composed of geometric figures	Attenuation based on Beer-Lambert's law	[18]

2.8.5 Light interception in fruit tree canopies

Light harvesting capacity of the tree canopy has an important role in enhancing the productivity of the fruit trees. There are different strategies for modelling the light interception in trees. Monte Carlo ray tracing method [69] is one of the most important effective tool in computing the path and interaction of multiple photons with the leaf surfaces until they leave the tree surface or get absorbed [70]. Later a new approach came out from this method called QuasiMS and was first used in the model L-KIWI. Some of the models focusing on light interception in the canopy of the trees are given below in Table 4.

2.8.6 Photosynthesis and respiration

Photosynthesis provide energy and carbon skeleton for various biological processes and its estimation is done by noting leaf area at a given amount of light in various time intervals of minutes to hours and then summed up for total daily photoperiod, estimation of canopy photosynthesis and usage of a very concise programming language called "L-systems". The different models useful in calculating canopy photosynthesis along with their use is given in Table 5.

2.8.7 Carbon partitioning in fruit crops

The general equation followed in plants regarding net photosynthesis is gross photosynthesis minus respiration in plants. When photosynthesis takes place in mature leaves, the photosynthates moves through the phloem in to the sink organs such as fruits, shoots and roots. Quali tree model used in *Prunuspersica* make use of carbon balance computation from the cumulative addition of photosynthesis from the carbohydrate reserves. After that, carbohydrates are allocated to each organ to fulfil the maintenance respiration and the growth of new leaf shoots and then to the organs where carbon supply didn't reach for maintenance respiration. After meeting all the requirements, finally the remaining carbon allocation gets done for the growth requirement of plants. Similarly the fruit tree models along with the principle of carbohydrate distribution is given below in Table 7.

2.8.8 Uptake of nutrients through roots and hydraulics in perennial fruit trees

To create a plant nutrition model, it is necessary to understand the distribution and architecture of roots [77]. According to [78], main factors regarding the carbon acquisition depends on light intensity while nitrogen uptake depends on its concentration in the soil. Some of the functional structural plant models and plant based models which has been integrated with the nutrient modelling are found in peach [79] and in grapevines [80], [81]. Pipe model theory can be used to model xylem circuit in which stems as well as branches are considered as the assemblage of pipe units each supporting one leaf [46]. Some of the models like L-KIWI employs an aspect-oriented approach considering water flow which takes into account leaf transpiration fluxes, leaf water potential and soil water potential.

Table 5. List of models useful in calculation of canopy photosynthesis with its purpose along with the references are given below

Name of the model/Approach/Strategy used	Purpose	References
Big leaf model	Used to estimate canopy photosynthesis as a daily canopy light response to daily intercepted radiation based on incident radiation and fractional interception using Beer's law and exposed leaf photosynthesis	[72]
"L-Systems	Base on plant growth pattern, it can calculate light interception and canopy photosynthesis and was first used to model a peach tree	[73]
Farquhar-von Caemmerer-Berry (FvCB) model	Biochemical model of photosynthesis of C3 plants using light responsive curve	[74]
Coupled approach	It considers environmental and leaf parameters as well as stomatal conductance (g_s).	[75]

Table 6. List of models useful in carbon partitioning along with the principle by which the carbon flow is based on and the references are given below

Name of the model	Principle by which the carbon flow is based on	References
LIGNUM	Functional balance (Nikinmaa, 1992) with pipe model hypothesis (Shinozaki *et al*. 1964 *a*) describes the relationship between biomass and tree cross-sectional area	[34]
INCA	Potential source: carbohydrates pool and sink demands	[35]
L-PEACH	Potential growth	[30]
L-KIWI	Carbohydrate availability from sources	[31],[45]
L-ALMOND	Location of sources relative to sink with tree architecture and the resistance between source and sink	[60]
L-PEACH	Carbon transport resistance allocation model (C-TRAM) (Prusinkiewicz*et al*. 2007)	[30]
L-system approach	Munch hypothesis (Münch, 1927) Michaelis–Menten sources and sinks (Thornley and Johnson 1990)	[76]
SIMWAL	Based on proportional model (Wilson, 1967), photosynthates allocated to each sink were proportional to its demand without exceeding it	[66]

2.9 Phenology Based Models in Perennial Fruit Crops

Perennial fruit trees responds to the environmental cues at different rates. Temperature, solar radiation and water availability are assumed to be the key regulators of plant phenology [82]. For crop management practises including irrigation, fertilisation, pesticide application and harvesting, planning at the farm scale and assessment of the phenological stages is crucial [83], [84], [85], [86]. When pesticides and fertilisers are applied more effectively at the right time and irrigation &crop harvesting activities are planned properly, production costs and environmental risks are decreased to a great extent and the realisation of these objectives are met by phenological models [87]. The 1950s witnessed the first time introduction of the concept “growing Degree Days” for the creation of phenological models [88]. The chilling hours model, which dates back to the 1800s is the most reliable way to calculate how many units of low temperature are required to break a plant's absolute dormancy and this model assumes that effective temperatures fall between 0 and 7.2 degrees Celsius, and that each hour at these temperatures counts as one chilling hour and gets accumulated throughout the dormant period [89]. With the advancement of technologies for meteorological data recorders, simulation models for the dependence of plant growth and development on weather have been developed in the field of horticulture.

Spring apple phenophases are facing the consequences of global warming and recently the gradual increase in the warm temperatures in the late winter or the early spring accelerates their premature development resulting in breaking of its endo and ecodormancy and its susceptibility to subsequent frost [90], [91]. [92] evaluated the phenological dynamics and late-spring frost risk on apple trees (*Malusdomestica*Borkh. cv. Fuji) in the Loess Plateau of China, taking into account the entire phenophase of apple trees in spring using four phenological models and the quantification of late spring frosts with two frost indices like AFD (accumulated frost days) and AFDD (accumulated frost degree days). [93] reported a novel simulation model (SIMBA-POP) based on the cohort population ideain order to forecast phenological patterns of the population and harvest dynamics in banana cropping systems. The model was calibrated and verified using field data from the French West Indies (Guadeloupe and Martinique) for Musa spp., AAA group, cv. Cavendish Grande Naine. It is capable of predicting banana harvesting dynamics (date and quantity of harvested bunches) that vary over time pretty accurately. In order to anticipate the yield of jujube (*Zizyphusjujuba*) orchards of various ages, [94] improved the WOFOST model by using the total dry weight (TDW) of new organs (initial buds and roots) and the outcomes showed that one of the crucial factors for precisely predicting the output of these fruit trees is the age of the orchard. Additionally, WOFOST proved effective at simulating the stages of phenological development of ripe fruits 2 to 3 days ahead of field observations.

2.10 Epidemiological Models of Fungal Diseases in Fruit Crops

Climate change is the root cause for various diseases in fruit crops. According to [95], the climate has a substantial impact on plant diseases since it may change the physiology and resistance of the host as well as the rates at which pathogens develop. Epidemiology deals with the interaction of host, pathogen and environmental factors which forms the back bone of disease triangle. There are multiple reasons behind the formation of a disease in plant by an invading pathogen and its pathogenicity. Abiotic stresses including heat and drought can change general defence mechanisms that impair plant resistance in addition to increasing plants' vulnerability to infections [96]. Any pathogen can only survive in a specific range of temperatures, and its experiencing temperatures on a particular location can also affect the pathogen's production times [97]. Similarly one of the major factor such as precipitation also affects the dynamics of plant diseases by changing the physiological makeup of plants as well as the pathogens' capacity to live, spread, and infect hosts [98], [99]. When predicting the growth of grapevine plants and the spread of powdery mildew, [100] suggested a detailed deterministic simulation model that takes into account air temperature, wind speed, and direction as climatic inputs. One of the most dangerous diseases of stone fruit is brown rot, which is caused by *Moniliniaspp* and it is prevalent throughout all temperate zones and affects species with significant economic significance such as peach, plum, apricot, cherry, and almond [101]. A Susceptible Exposed Infectious (SEI) model was suggested by [102] to characterise the temporal dynamics of brown rot spreading in fruit orchards and assess the resulting marketable yield. [103] integrated compartmental epidemiological model for brown rot diffusion with fruit tree growth model with major emphasis on agronomic practices over fruit quality. They suggested giving a moderate water stress in the final weeks of fruit development which in turn gives a moderate fruit load and thereby decreasing the spread of brown rot in the orchard. Compartmental SIR- type (Susceptible-Infected-removed)epidemiological models in stone fruits simulating various epidemic patterns and the detailed analysis of possible impacts of climate change on the disease induced yield loss has been reported by [104]. This smart climate-driven model could simulate the epidemic patterns with temperature and precipitation as the key factors behind the epidemic and also dealt with the synergism of pathogen vulnerability with that of varying phenology of the peach tree. CIPRA (computer centre for agricultural pest forecasting software) software was conceptualised in the year 1960s and it helped the users with the forecasting of 13 insects, two diseases and two storage disorders and it has improved over the past 13 years in giving out detailed epidemiological models based on air temperature, relative humidity and leaf wetness duration [105].

2.11 Insect Control Forecasting Model in Fruit Crops

Insects cause the greatest crop losses (34%) among the several types of pests, followed by diseases (31%), weeds (27%), and viruses (8%), in that order [106]. Pest control in the fruit orchards primarily relied on the use of broad-spectrum pesticides in the past, which were having lot of negative effects like the extinction of beneficial insects &microorganisms, resurgence of more threatening forms of pests, potential threats to pesticide users as well as the bystanders and vicious biomagnification of the chemical compounds in the food web present in the ecosystem. Policy makers have been expressing their heightened fears surrounding these issues which sparked alternate ways to minimise the usage of pesticides and the adoption of integrated pest management [107]. One of the goals under European Union green deal is the implementation of biodiversity strategy to 2030 to combat such dreadful usage patterns of harmful chemical compounds in crops. Population of natural biological controls should be maintained as a healthy way to manage the rising pest menace and incorporate farmer's decisions in the application in a collective manner towards the journey of sustainable agriculture. So far we don't have location specific ecological models to predict natural pest control, but only a generic model based on landscape composition or configuration which limits the predictive management tool for stakeholders [108]. [109] studied generic landscape models of natural pest and biocontrol agent in cherry trees with aphids and pollen beetle as natural enemies and reported the difficulties of enhancing the predictive power of generic models without using spatial planning of agricultural areas, inclusion of soil conservation systems like conservation tillage and specific association between crop, pest and biocontrol. Insect forecasting models involves the consideration of various inherent characteristics of insects such as its developmental stages as well as the influential environmental and host-related factors [105]. [110] reported about the SOPRA forecasting model used in fruit orchards of Switzerland with the main focus on the optimisation of monitoring time of pests, management and control measures of eight major insect pests such as rosy apple aphid, European apple sawfly, codling moth, apple seed moth, pear psylla, European cherry fruit fly, apple blossom weevil and summer fruit tortix moth. This model utilizes time-varying distributed delay approaches (effect of environment factors on insect phenology may not occur suddenly and can vary over time). Phenology based models considering the environmental variables like air temperature, soil temperature and incident solar radiation on an hourly basis were established. Phenology has a direct relationship with the intricate decision support systems, details of the age structure of insect pest population present in the locality and plant protection products to be used. Through the website www.sopra.info, results from this model will be available to growers and consultants.

2.12 Innovative Probabilistic Machine Learning Models in Fruit Crops Replacing Conventional Mathematical Models

Probabilistic models are statistical approaches which helps in comprehensive understanding of uncertainties associated with predictions of possibility of future results and it offers critical data for strategic decision making process. In order to identify novel solutions for agricultural problems, contemporary environmental and precision agriculture research has recently combined with machine learning (ML) techniques [111]. One of the most crucial components of

Table 7. List of CNN models, their objective and the technique which it uses along with the references are given below

Name of the CNN model	Objective	Technique which it is based on	References
modified MobileNet model	Automatic detection of avocado fruit disease	Image processing technique	[127]
V2IncepNet	Detection of lesion areas on mango leaves and identification of level of infection and diagnosis of the anthracnose disease.	Pattern identification and image characterisation	[128]
3-layer Convolutional Neural Network (CNN)	Automated classification and grading of eight cultivars of harvested mangoes based on quality features such as color, size, shape and texture	images rotation, translation, zooming, shearingand horizontal flip	[129]
Yolo conventional neural network	Automatic identification of citrus huanglongbing	Deep learning based method and sensory detection	[130]
Banana squeezeNet	Identification of leaf diseases such as bacterial soft rot, cordana, panama, pestalotiopsis, sigatoka and pest attack of banana fruit scarring beetle, pseudostem weevil and banana aphids	Deep learning and Bayesian optimization in effectively diagnosing banana leaf diseases from images without any human intervention	[131]
ESDNN (Ensembled stack deep neural network)	Helps in the earlier automatic detection of mango leaf diseases such as powdery mildew, anthracnose etc with great accuracy	AI based solution to detect and classify leaf diseases	[132]
Yolo papaya	Detecting diseases in fruits at an early stage is crucial to mitigate losses and ensure the quality and health of fruits.	YoloV7 detector with the implementation of a convolutional block attention module (CBAM) attention mechanism	[133]

machine learning and artificial intelligence are artificial neural networks and they are modelled after the structure of the human brain and operate as though they were made of interconnected nodes where simple processing operations are performed [112]. With the help of this model, people were able to address a variety of practical issues that had previously proven to be challenging [113], [114], [115]. Deep learning, one of the advancing areas of data science is an extension of research on artificial neural networks including the convolutional neural network [116], the recurrent neural network [117] and the deep belief network [118]. Convolutional neural networks (CNN) was proven to be a promising technique that outperforms current popular image-processing methods in terms of precision and classification accuracy [119]. CNN has got various applications ranging from fruit flower detection, fruit detection at various stages, fresh fruit production, and fruit harvesting & grading contributing a key role in each link of fruit production [120]. Some of the applications of CNN in fruit crop is given below in Table 7. The use of computer vision, machine learning, and IoT applications will assist boost productivity, enhance quality and ultimately increase the profitability of farmers and related industries [121]. Machine learning models were used as an alternative tool to evaluate and validate prediction models for date palm mite infestation based on meteorological variables and physiochemical properties of Khalas and Barhee dates [122]. Similarly there are reports of advantages of machine learning models in fruit crops regarding metabolomics selection based machine learning which improves fruit taste prediction [123], identification of iron chlorosis in plants using deep learning [124], integration of remote sensing and weather variables for mango yield prediction with machine learning approach [125] and so on. Artificial neural networks with internet of things (IoT) devices is very much useful in enhancing the productivity and efficiency of greenhouse plants by the automatic disease and pest identification as well as the greenhouse climate management [126].

2.13 Application of Crop Modelling in Fruit Crops in the Current Scenario

Almond:

1. On the basis of shortwave and temperature data, remote sensing methods based on surface energy flow models, such as the two-source energy balance (TSEB) model coupled with high spatial resolution of sentinel-2 and the high revisit time of sentinel-3 (daily) were employed to calculate actual evapotranspiration (ET_a) in almond orchard under four different orchard irrigation regimes [134]
2. In order to estimate almond fresh weight at the tree level, a convolutional neural network (CNN) model with a spatial attention module was used to take the multi-spectral reflectance picture replacing the traditional linear regression and machine learning methods for accurate and robust tree level yield estimation [135]
3. The FAO56 dual-K_c technique and the SIMDualK_c model were used to compute the soil water balance for each orchard and estimate the crop evapotranspiration (ET_c). The model accurately predicted the soil water contents in fruit trees such as almond. Olive, citrus and pomegranate across two growth seasons in distinct fields by validation followed by derivation and evaluation of K_c(crop-coefficient) and K_{cb}(basal transpiration coefficient) standard and actual crop coefficients in a water saving perspective for crops using dual-k_c approach [136]

Apple:

1. A fruitlet growth model to predict thinner response of apple has been reported by [137]. The model relies on the idea that a fruit will fall away if its rate of growth during the measurement period is less than 50% of the rate of the fastest-growing fruit on the tree during the same growth period, whereas it will persist if its rate of growth exceeds 50% of the fastest-growing fruit.
2. A convolutional neural network (CNN) model detects apple plant diseases using leaf images using publicly available dataset plant village in the identification of scab, black rot and cedar rust in apple with smaller number of layers and lowered computational burden [138]
3. STICS model was used in simulating apple phenology &yield and to quantify the yield loss with frost damage during flowering at Shaanxi province so as to mitigate frost disasters in apple production [139]

Apricot:

1. Mathematical models were used to mitigate reduced fruit quality due to mildew, browning and sand dust from natural drying under low temperatures and humidity through three different methods of drying such as natural drying under desert conditions, ventilated drying in air-drying house and hanging them on trees. The Wang and Singh model provided the most precise explanation of the apricot's natural-environment drying mathematical model [140]
2. Numerical models that use experimental data on the emergence of plants from a deep dormant condition and the combined effect of temperature and photoperiod on the process of spring development has been reported by [141] so as to predict when apricot trees will flower and also in increasing the profitability of fruit production

Banana:

1. The long-term dynamics of the banana crop at the field scale were simulated using a phenological model. According to simulations, the nematicide application programme, climate and banana field planting date all affect the mean fosthiazate concentration in fruits. Utilising this technique will assist farmers in reducing the amount of harvested bunches that have fosthiazate residues above a threshold [93]
2. An improved agro deep learning model detects panama wilt disease which helps in predicting the severity of diseases and its consequences based on arrangement of leaf color and shape changes. It helps farmers to rely on accurate decision support systems in a timely manner and prepare them how best to tackle the problem [142]

Cherry:

1. CRPSM, a transpiration-yield model on the basis of transpiration competition between tree crop and grass cover accurately described differences in tree growth and production [143]
2. A Growing Degree Day Based (GDD)-IPM model was used for the control of Spotted Wing Drosophila, a major insect that has a negative impact on Michigan's tart cherry output and it helps in the identification of the best time to apply pesticides based on a mix of partial budget analysis, daily meteorological data, and phenological data [144]
3. Based on a three-dimensional (3D) cherry tree canopy point cloud model fused by several sources, a method for forecasting canopy light distribution in cherry trees was put forth and it provides technical support for scientific and judicious cherry tree pruning [145]

Citrus:

1. Different micro irrigation systems such aspartial root-zone drying techniques (PRD) which involves exposing half of the root system in drying state and remaining roots in wetted state so as to alter the irrigated roots on time and regulated deficit irrigation (RDI) While water is typically supplied at levels below the maximum rate of crop transpiration throughout specified growing season times. FAO-56 agro-hydrological model is used to evaluate the eco-physiological response of citrus orchards to such different water-saving irrigation management strategies [146]
2. Using a non-linear neural-network model and an ensemble system, an integrated sugar-content prediction model in three species of citrus genus was developed. This is indeed a non-destructive technique of accurately measuring the sugar content of the fruits and the producers can supply high quality, high value fruits [147]

Dragon fruit:

1. Michaelis-Menten based respiration model extended with a modified Arrhenius equation incorporating the Boltzmann distribution fuctionwas used for the respiration kinetics of dragon fruit under different storage conditions [148]
2. RESNET 152, a deep learning convolutional neural network was utilized to identify the mellowness of dragon fruit and determination of its harvest time [149]

Grapes:

1. SimulateurmuLTIdisciplinaire pour les Cultures Standard (STICS) is a dynamic, feasible decision support tool in short and long term strategic planning in Portugeese viticulture considering the impacts of climate change on several site-specific parameters for climate, soil and several management practices and it simulates the phenological stages, yield and water stress in grapes thereby helping in carrying out the vineyard operations and wine making practices efficiently [150]
2. STICS crop model was used to assess the potential impacts of heat waves in wine growing regions of Europe and dealt with the mitigation measures of upcoming heat waves in near future [151]
3. AquaCrop model simulates canopy cover, actual evapotranspiration, total soil water content, biomass and fruit yield of table grapes vineyards and it has an important role in the evaluation of irrigation scheduling by the farmer as well as to assess the water productivity in the arid and semi-arid regions where availability of water is a major problem [152]
4. In order to create higher-quality wine, the grape wine business needs accurate fruit counts to help with planning and decision-making prior to harvest and due to the current fruit tracking and counting techniques with low real-time performance and the vast shape variations of cluster-like fruits, there are currently no reliable counting techniques available. A lightweight YOLOv5s cluster detection model based on channel pruning algorithm that reduces model parameters and complexity in detection coupled with SORT algorithm enables real time time tracking and counting of grape clusters in the field based on video datas [153]
5. A real time grape disease identification model in the field based on improved YOLOXS (GFCD-YOLOXS) has been reported by Wang *et al*. (2023). This model utilizes a dataset of 11,056 grape disease images in 15 categories. Two modules such as FOCUS (reduces the lack of information related to grape diseases) and the CBAM/ Convolutional Block Attention

Module (at the prediction level focusing on key features of grape diseases and mitigating the influence of natural environment) are the components of this model which enhances its fastness as well as efficiency in the identification of diseases.

Mango:

1. V-Mango a functional-structural plant model broadened the simulation of cultivation practices of mango by modelling complex architectural development of mango tree over several growing seasons using a multi-scale approach. Different sub-models such as thermal time models, eco physiological models formalize the growth and development of individual growth units, inflorescences & fruits on an daily scale and fruit growth respectively [154]
2. A novel active mathematical model was created using an enzyme kinetics-based respiration rate model linked with the Arrhenius equation under active conditions to construct an active modified atmospheric storage systems (MAS) for 100 kg of mango and they were handled and stored in the farm using the designed active system at a temperature of 27°C with the main goal to establish an early dynamic equilibrium state inside the MAS system having ideal amount of gas concentrations [155]

Mangosteen:

1. Mathematical models using fractals and computers were used in accurately understanding the growth and form complexity of gamma irradiated plant root systems in Mangosteen [156]
2. ResNet50, a deep convolutional neural network was utilized for classifying the ripeness of mangosteen and classifying them accordingly to the market segments such as export market, domestic market, local market and ungraded mangosteens [157]

Olive:

1. A stochastic weather generator model, ClimaSG was very useful in the calculation of crop water requirements and irrigation designs & planning under low density rainfed (LD) and super high density irrigated (SHD) olive orchards in Spain [158]
2. U^2 net deep learning model has been used in Olive trees in China to monitor its growth and predicting the fruit yield thereby helping in the robust monitioring and management of orchard trees [159]
3. Olive can, a process based simulation model of olive orchards has been used for analysing the role of cover crops for minimising the erosion rates [160]

Papaya:

1. In order to forecast fruit size and harvest dates, one must be aware of the papaya fruit's growth dynamics and its thermal requirements measured in Growing Degree Days (GDD) from bloom to ripening. Considering this, research work carried out by [161] developed the best model representing papaya fruit growth and the GDD necessary for fruit ripening in four cultivars such as BH-65, Calimosa, red lady and Siluetchosen for their diverse vigour and fruit size. The findings demonstrated that papaya fruits develop along a straightforward sigmoid curve and using the Gompertz equation helps in describing papaya fruit growth due to its simplicity and excellent fitting results. Also the use of heat units was found to be more useful tool in predicting harvest dates than counting the calendar dates.

Passion fruit:

1. DynamiCROP, a dynamic and crop-specific pesticide uptake model in passion fruit takes into account the amount of spray deposition of difenconazole, tebuconazole and deltamethrin on plant surfaces, uptake mechanisms, dilution owing to crop growth, degradation in plant components and decrease due to food processing (peeling) as well as the time between pesticide application and harvest and the time between harvest and consumption [162]. This model is also useful in advising farmers regarding the judicious choice of pesticides and its application schemes.

Peach:

1. Compartmental SIR- type epidemiological (susceptible infected-removed) model has been utilized by [104] in peach for

simulating the different epidemic patterns and for evaluating the impacts of climate change in brown rot disease in peach orchard. The model predicts temperature and precipitation as the main causal agents for brown rot epidemics. In this study, a synergism between alterations in the crop phenology and vulnerability to pathogens has also been studied.
2. Ordinary differential equations (ODE) kinetic model in peach has been reported by [163] in simulating the different developmental stages of peach with the accumulation of different sugars. This model made use of two approaches such as genotype based strategy (GBS) and population based strategy (PBS) in developing reliable gene to phenotype models.
3. The effect of rootstock micropropagation method as an alternative to conventional grafting of peach varieties with rootstocks propagated on cuttings has been reported by [164] using linear mixed-effects models. The main objective of this study was to control the variance bought out by environmental as well as cultural factors on the agronomical results in the woody plants with long life cycle.
4. Vis(visible)-NIRS (near-infrared spectroscopy) collaborated with individual cultivar specific datas helps in the accurate non-destructive internal fruit quality (dry matter content) and maturity assessment (index of absorbance, I_{AD}) of seven peach cultivars [165]

Pecanut:

1. Growth models involving heat units is a very useful tool in predicting the different nut growth stages in pecanut by taking in to account of three phenotypic traits such as shuck, shell and embryo. Comparison of different non-linear growth models reported by [166] indicated that the logistic model was found to be efficient in modelling shell growth and Gompertz model fits best in embryo development modelling. Their study found to be a pivotal role in the analysis of role of irrigation in the water stages of pecanut and thinning at the late water stages prior to nut filling stages. Minimum use of pesticides at the shell lignification stage was also suggested as a part of this study.

Pineapple:

1. A process-oriented model called ALOHA PINEAPPLE v. 2.1 simulates the growth, development, and production of the mother plant crop of the pineapple variety known as "Smooth Cayenne." The model runs on a daily time step and takes observation of inputs like daily meteorological data, characteristics of the soil profile and management information [167]
2. The SIMPIÑA model, which simulates the growth and development of the "Queen Victoria" pineapple cultivar depends on stress brought on by nitrogen and water deficiency into account [168]
3. The price of pineapple is valued by its sweetness in Thailand whose determination has been made possible with the help of Alexnet deep learning models in categorizing in to different sweetness level based on physical attributes [169]

3. CONCLUSION

The major advantage of functional structural plant model is the integration of most basic physiological processes such as photosynthesis, respiration, nutrient allocation and branching processes using techniques like pipe model, L system of framework, semi-markovian models. However further researches should be done in the line of root architecture because it is complex in the sense that the development of roots are not represented on the basis of elemental repeats. Phenology based models are more robust in simulation of the growth and development of trees with the climate. They help in efficient spring frost warnings and harvesting dynamics of the horticultural produce. Epidemiological models gives out the temporal outbreak of diseases with the interacting environmental factors. Compartmental epidemiological model in fruit crop considers the integration of agronomical practices with the fruit quality parameters with respect to the diffusion of disease in the fruit orchard. It helps in enhancing the monetary returns of the farmers. Insect forecasting models should progress from generic to specific level giving due consideration to the beneficial insects present in a particular landscape and the decision making process of farmers & stakeholders in the use of plant protectants. The rise of innovative machine learning models helps in the popularisation of precision agriculture in developing countries in near future.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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