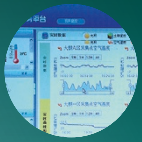
Agriculture Automation and Control

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Advanced Automation for Tree Fruit Orchards and Vineyards

Springer

Agriculture Automation and Control

Series Editor

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The ultimate goal of agricultural research and technology development is to help farmers produce sufficient foods, feeds, fibers, or biofuels while at the same time, minimize the environmental impacts caused by these large scale activities. Automation offers a potential means by which improved productivity, resource optimization, and worker health and safety, can be accomplished. Although research on agricultural automation can be found in the published literature, there lacks a curated source of reference that is devoted to the unique characteristics of the agricultural system. This book series aims to fill the gap by bringing together scientists, engineers, and others working in these areas, and from around the world, to share their success stories and challenges. Individual book volume will have a focused theme and will be guest-edited by researchers/scientists renowned for their work within the respective sub-discipline.

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Editors

Advanced Automation for Tree Fruit Orchards and Vineyards

Springer

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Preface

Modern tree fruit orchards and vineyards constitute complex production systems exposed to highly dynamic and stochastic natural, financial, and societal forces and face demands for increased production using fewer resources with reduced environmental impact. Successful operation of orchards and vineyards under these conditions necessitates careful and extensive use of state-of-the-art automation technologies and careful planning of future operations (e.g., training systems when replanting) that can be enabled by knowledge of emerging technologies and future trends. Also, improving existing automation technologies and developing novel future systems cannot be accomplished without a working understanding of the tree and vine biological production systems, their management needs, and the capabilities and limitations of existing automation systems. This book aims to provide the necessary knowledge to achieve the above goals to readers who don't necessarily have engineering or horticultural backgrounds.

In Chap. 1, the book introduces basic tree and vine physiology, water and nutrient propagation through the soil-plant-atmosphere continuum, and pressures from pests and diseases. The establishment of modern orchards and vineyards using various training systems is also presented.

In Chap. 2, basic canopy management operations such as hedging and pruning are presented, emphasizing robotic pruning operations. Also, existing and emerging canopy sensing technologies are discussed.

Water management in orchards and vineyards is discussed in Chaps. 3 and 4, respectively. Principles and technologies for remote and proximal sensing for soil and plant water and nutrient status are presented, as well as state-of-the-art methods to determine the necessary irrigation inputs, including model-based decision support systems. Current and emerging technologies for sensing and actuation systems for precise automated application of inputs are discussed in detail.

Chapter 5 presents principles, methods, and hardware and software technologies to sense (detect, classify, and quantify) pests and disease and discusses state-of-the-art actuation technologies for targeted pest and disease control; ground and aerial platforms are included.

Chapter 6 discusses crop load management. Fruit trees generally bloom more flowers and set more fruit than they can support to grow the desired yield of high-quality fruit. Precise crop load management practices aim to optimize the yield and specific desired quality parameters by reducing the number of fruits set and grown in a given tree. The chapter discusses the opportunities and challenges of robotic solutions for tree fruit production with modern planar tree canopy management, including the importance of modern tree canopy systems, robot-canopy interaction, robotic system control, in-field sensing for object detection, and three-dimensional (3D) reconstruction, and a case study on the robotic branch pruning for apples with modern tree canopies.

Chapter 7 covers harvesting mechanization by providing a general overview of many of the fundamental factors and challenges surrounding mechanical harvesting and the development of mechanical harvesting systems, plus providing some examples of various current and possible future concepts.

Chapter 8 covers the topic of autonomous platforms. It discusses how robots are used in precision agriculture for orchards and vineyards to automate and simplify tasks. Topics include ways in which platforms track their positions, such as GPS; what types of sensors are generally used on top of location; and how this data is used for decision-making and human safety within the navigation and mobility concept. It also discusses other high-level topics, such as path planning and optimization and fleet management, to explain the necessary aspects that play behind the scenes. The chapter closes with examples of existing commercial and emerging autonomous systems for orchards and vineyards.

Chapter 9 discusses the principles of farm management information systems, i.e., computation, communication, and algorithmic sub-systems, that integrate sensing, actuation, data management and analysis, knowledge of horticultural practices, and decision-making to help automate the operation and management of modern orchards and vineyards. Topics include types of data and information, infrastructures, architectures, standardization, data ownership and sharing, and decision support system technologies.

Finally, Chap. 10 discusses the economics of automation related to fruit and grape production, the impact of automation on the environmental footprint of production, and the societal impacts of increasing automation on growers, farmworkers, and rural communities in general.

As stated above, this book aims to reach a wider audience. To achieve this goal, the book introduces the fundamental functions (physiology) of fruit trees and grape vines. It also tries to cover the fundamentals of automation for managing both orchards and vineyards in a systematic, integrated manner that highlights commonalities and differences. Furthermore, it discusses both current commercial and emerging automation technologies. Our wish—and hope—is that this book will prove helpful to a broad audience of readers that spans undergraduate and graduate students, researchers, engineers, and, hopefully, farmers, policymakers, and stakeholders in specialty crops production.

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Contents

Chapter 1
Fundamentals of Tree and Vine Physiology

Alexander Levin and Theodore M. DeJong

Abstract Orchards and vineyards can be considered biologically based solar energy-capturing systems designed to capture solar energy and use that energy to convert CO_2, water, and nutrients into edible fruit products. However, most of the water that is inadvertently needed for this process is not used in making fruit but passes through the trees or vines in exchange for taking up CO_2 from the atmosphere to make carbohydrates that are used to transport energy around the plants and construct the plants and their fruit. The distribution and use of carbohydrates by the trees and vines are governed by genetically determined patterns of development and growth of their individual organs, the environment surrounding organs, and competition for carbohydrates among organs. The architecture of trees and vines is governed by the genetically determined growth habits of their branches and built-in responses to manipulations of their canopies, such as pruning. It is now understood that tree and vine canopies can develop naturally strong structures without pruning but that pruning can be necessary to optimize conditions for high-quality fruit production and to facilitate efficient orchard or vineyard operations.

1.1 Introduction

1.1.1 Specialized Solar Energy Collection

From an engineering perspective, a fruit or nut tree orchard or a vineyard can be viewed as a massive network of solar energy collectors. The individual solar collection plates (grana stacks) are located in chloroplasts, green microscopic structures

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within biological cells of the leaves (Taiz et al., 2015). Each leaf contains thousands of chloroplasts that function as solar energy cells. Trees or vines, in turn, support and display thousands of leaves and are arrayed and managed in an orchard or vineyard to efficiently capture and/or distribute light within canopies in a manner that is intended to either maximize total light interception or optimize light interception and distribution to simultaneously manage both fruit quality and yield. In orchard crops such as nuts, in which there are minimal premiums for size or light exposure-related quality characteristics, the emphasis is on maximizing yield and thus maximizing light interception. In fruit crops in which there are premiums paid for size and quality, light exposure of the fruit or fruit-bearing shoots is important. Thus, managing light distribution within canopies can be as important as the total light interception of the orchard or vineyard canopies.

The solar energy cells (chloroplasts) only function if they are in aqueous solution, so leaves are specially designed to maintain the solar cells in a hydrated state inside the biological cells even though leaves are usually exposed to dry ambient conditions (Taiz et al., 2015). In this analogy, the woody framework of the tree and trellis structures in orchards and vineyards can be viewed as providing the structure by which the plants are capable of exposing optimal numbers of solar cells to light energy. In addition to providing the structural framework for optimum light exposure, the wood and bark provide a vascular tissue for transporting water and nutrients to the leaves and chemical energy (photosynthates) from the solar cells (chloroplasts) in the leaves to other parts of the plant. The efficiency of a tree or vine as a solar energy collector network depends on the capture and conversion of light energy into chemical energy (photosynthesis) and the subsequent transport, storage, and utilization of that chemical energy for fruit production. This concept is supported by the fact that maximum yields of orchards, when optimally managed, have been shown to be directly related to the percentage of daily solar radiation intercepted (Lampinen et al., 2012; Palmer et al., 2002; Wunsche & Lakso, 2000). Similarly, vineyards with higher amounts of exposed leaf area per vine or more closely planted rows – resulting in more exposed leaf area per hectare – are very productive and/or produce high-quality fruit (Dokoozlian, 2009; Kliewer & Dokoozlian, 2005).

Looking at the functioning of trees and vines from this perspective is useful for both scientific and practical horticultural reasons. Because of the importance of photosynthesis to the efficient functioning of plants as solar energy collectors, scientists have been intensively studying the process of photosynthesis for more than 100 years with the hope of increasing its efficiency. However, there is little evidence that scientists have or will be able to increase this efficiency in crop plants in the near future (Horton, 2000). Nevertheless, there is substantial evidence that fruit trees naturally distribute nutrient resources, adapt leaf photosynthetic competency, and adjust leaf angles in different parts of their canopies, to optimize use of resources for capturing sunlight as it passes through their canopies (Auzmendi et al., 2013; DeJong & Doyle, 1985; DeJong et al., 1989; Niinemets, 1995, 1997; Rosati et al., 1999, 2000, 2002). On the other hand, grapevines are naturally climbing lianas and in nature are adapted to climb on top of other plants or structures. Thus, each leaf is adapted to operate independently and take advantage of all light that it can intercept (Gamon & Pearcy, 1989). Indeed, considering that cultivated grapevines are most often grown on a trellis designed to display foliage in a particular way and that vineyards consist of discontinuous canopies oriented in a fixed row direction, leaf angle and azimuth are often a function of vineyard trellis design and row orientation (Mabrouk et al., 1997).

Trees and vines have evolved to optimize these processes in the context of survival and reproduction in diverse natural environments. So why should horticulturists and orchard/vineyard managers be concerned about studying and understanding photosynthesis and the distribution of photosynthates in trees and vines? The horticulturist's objective is to optimize orchard/vineyard conditions such that trees and vines carry out photosynthesis and efficiently distribute and use photosynthates toward obtaining an economically valuable crop. The orchard or vineyard manager's objective is to optimize cultural inputs that influence these optimal conditions. While the former is more ecophysiological and the latter more operational, both objectives require a basic understanding of the plant's fundamental processes and the factors that influence them.

1.1.2 Photosynthesis

Simply summarized, photosynthesis is the process (Fig. 1.1) by which light energy from the sun is captured by green pigments in plant tissues (chlorophyll, mostly found in leaves) and converted into chemical energy. This chemical energy is then used to combine carbon dioxide gas (CO_2) and liquid water (H_2O) into simple carbohydrates that eventually become more complex sugars ($[CH_2O]_n$). These sugars are exported from leaves and distributed throughout the plant to be used as an energy source for growth and development. However, they are also stored for later redistribution and use. The reverse process, whereby energy is recovered from these sugars (and oxygen gas released), is called respiration and is common among all plants and animals (Taiz et al., 2015).

The actual photosynthetic process is a complex set of reactions involving many of the nutrients green plants require. For example, nitrogen (N) is a constituent of photosynthetic enzymes and chlorophyll; phosphorus (P) is important in the energy

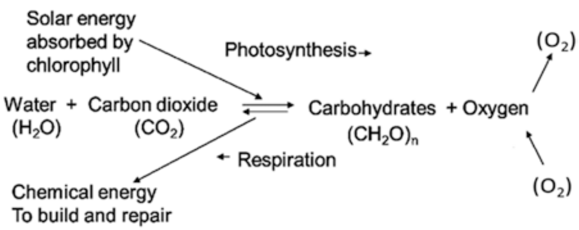

Fig. 1.1 Diagrammatic summary of photosynthesis and respiration

transfer process; magnesium (Mg) is an essential part of the chlorophyll molecule; potassium (K), iron (Fe), manganese (Mn), and other nutrients play important roles in specific photosynthetic reactions (Taiz et al., 2015). The carbohydrate products of photosynthesis are collectively called photosynthates. A principal product is glucose, a six-carbon sugar. It is transformed into other simple sugars, i.e., fructose, sucrose, and sorbitol, a sugar alcohol. In most plants, sucrose is the predominant carbohydrate transported from the leaves to other parts of the plant; however, in most rosaceous fruit trees, sorbitol is the primary transported carbohydrate (Bieleski, 1982).

The CO_2 for photosynthesis comes from the air surrounding the leaf, and the water comes up from the soil through the plant's vascular system. CO_2, which makes up only about 0.040% of the earth's atmosphere (~400 ppm in air), diffuses through the stomata located in the lower epidermis of almost all fruit tree and grapevine leaves. Stomata not only allow entry of CO_2 into the leaf but also allow water vapor to escape from the leaf. Thus, to minimize water loss from the leaf (transpiration), the stomata have an active mechanism for controlling their opening to permit just enough carbon dioxide into the leaf to allow photosynthesis to continue without excessive loss of water (Taiz et al., 2015).

1.1.3 Interactions Between Photosynthesis and Water Use

During the daylight hours when photosynthesis occurs, stomata are open, and leaves lose (transpire) as much as 400 molecules of H_2O for every molecule of CO_2 that is absorbed depending on the ambient temperature and relative humidity (Taiz et al., 2015). The water that is lost from leaves is replenished by water transported through the tree or vine from the soil. If the soil around the tree or vine is moist, water also evaporates into the air directly from the soil. The total quantity of water lost by plants and soil is generally called evapotranspiration (ET) and crop ET (ET_c) in crop production specifically (Allen et al., 1998).

A vast majority of total ET_c is accounted for by plant transpiration. Accordingly, there has been increased research emphasis placed on developing plants with improved photosynthetic water use efficiency (WUE) due to increasing competition for water resources in many agricultural growing areas. However, most of this research has had limited success because photosynthesis can only be carried out in aqueous solution within leaf cells. The laws of physics (diffusion) govern the amount of water loss when stomata are open to allow CO_2 to enter the leaf to supply the photosynthetic process (Taiz et al., 2015; Blum, 2009). As a consequence, the primary research successes in increasing orchard and vineyard WUE have been achieved by improving irrigation delivery system efficiencies, such as changing to micro-irrigation systems that more precisely deliver water to trees and vine where they need it and scheduling irrigation so that water is delivered when the plants most need it (Blum, 2009; Auzmendi et al., 2011; Lopez et al., 2016; Marsal et al., 2016; Behboudian et al., 2011).

1.2 Factors That Influence Photosynthesis in Fruit Trees and Vines

1.2.1 Light

Since an orchard or vineyard's primary function is to be a solar energy farm, light is the most important driver of photosynthesis. However, there is seemingly a flaw in this system since photosynthesis of many individual tree leaves, as well as leaves of many other crop plants, is light-saturated at approximately one-third to one-half full sunlight if a leaf is exposed perpendicular to the sun's rays (Taiz et al., 2015; DeJong, 1983; Li & Lakso, 2004). In addition, the light saturation point of photosynthesis for a given leaf likely depends on the conditions under which it developed (Kriedemann, 1968). However, only leaves on the outer surface of a tree canopy are ever exposed to direct sunlight for long periods, and even those leaves are usually oriented vertically and often folded at the midrib. Thus, they only receive direct exposures for very short periods of the day as the orientation of the sun to the tree changes from east to west (DeJong & Doyle, 1985; Rosati et al., 1999). Each leaf, located in its zone of the tree canopy, has its own ever-changing light environment (DeJong & Doyle, 1985). Light is shared among leaves in deciduous fruit tree canopies so that most leaves in a mature tree function most of the day on the steep rather than the light-saturated portion of the photosynthetic light-response curve (Rosati et al., 2002). Light becomes limiting for photosynthesis along a gradient from the outer, exposed edge to the center of the foliar canopy, and often this gradient is depicted as a continuous reduction of light intensity toward the interior of tree canopies (Robinson et al., 1991). However, much of the light intercepted by many leaves is in the form of sun flecks, and the light exposure of interior leaves is a function of the amount of time leaves are exposed to sun flecks as opposed to being in shade (DeJong & Doyle, 1985). Thus, interior leaves contribute less photosynthates to the local fruit-bearing shoots to which they are attached, and those shoots develop less leaf area and are less productive than more exposed shoots. These shoots may eventually die if total light interception is below the threshold for shoot survival (Lampinen et al., 2011), reinforcing the importance of solar energy collection in a tree's economy.

Leaves of vines operate a little differently. Vines are by nature climbing lianas, and they are adapted to climb on trees and other structures. Thus, individual leaves of vines are generally adapted to be oriented perpendicular to prevailing sun rays and not "share" light with other leaves in a canopy. Accordingly, grapevines tend to have thicker leaves than deciduous trees, and their photosynthesis is light-saturated at higher light levels than deciduous tree leaves (Mullins et al., 1992).

1.2.2 Sink Strength

In horticulture, much attention has been paid to the question of whether photosynthesis of fruit trees and vines is strongly controlled by plant demands for carbohydrates, as opposed to environmental drivers of photosynthesis such as light (Neales & Incoll, 1968). Researchers have reported that photosynthesis can be substantially increased in the presence of high demand for carbohydrates by fruits in several fruit crops (Avery, 1975; Hansen, 1970; Maggs, 1963), and this led some researchers to assert that fruit demand for carbohydrates is a major factor controlling photosynthesis in fruit trees. Indeed, photosynthetic rates have been shown to be reduced in de-fruited grapevines (Downton et al., 1987; Edson et al., 1993). However, other research has indicated that the effect of fruit on photosynthesis can be relatively minor (DeJong, 1986). Close analysis of much of the literature reporting strong effects of crop load on photosynthesis indicates that those effects are mainly present when there are factors such as dwarfing rootstocks (Palmer et al., 2005) or girdling (Ben Mimoun et al., 1996; Harrell & Williams, 1987) that limit the flow of photosynthates to alternative sinks and cause a feedback-mediated reduction in carbohydrate movement from the leaves. While there may be a tendency for stomata to function less conservatively in controlling the ratio of CO_2 uptake to H_2O loss in the presence of fruit (DeJong, 1986), there does not appear to be strong evidence for crop load being a primary regulator of photosynthesis in the absence of some "artificial" mechanism that limits the capacity of alternative sinks to utilize photosynthates for growth. This corresponds with the concept that a plant species' success and survival in nature are expected to be associated with garnering as much carbohydrate resource as possible to grow and compete for space in addition to reproducing (Stephenson, 1981).

1.2.3 Temperature

Photosynthesis functions optimally at leaf temperatures between about 20 and 30 °C in many temperate deciduous species (Ro et al., 2001), though this optimum range may shift depending on the conditions under which the leaf developed (Mullins et al., 1992; Kriedemann, 1968). While the temperature-based limits for temperate deciduous trees and vines are dictated most often by winter and spring cold events or lack of winter chill, rather than photosynthetic temperature optima, growing season temperatures can influence fruit quality and yield through effects on photosynthesis. Crops that have fruits with high sugar contents, such as many stone fruits and grapes, tend to be sweeter in climates where daytime maximum temperatures are greater than 30 °C, whereas many starch-accumulating fruit species do better in areas where temperatures rarely exceed 30 °C. More research is needed to explore whether this is related to the photosynthetic process or downstream carbohydrate metabolism in these species. It is important to note that even at leaf temperatures approaching 45 °C, photosynthetic rates of field-grown grapevine leaves may still be 50% of their maximum (Mullins et al., 1992). Moreover, even in regions where maximum temperatures often exceed 30 °C, these temperatures usually only occur for a relatively short period in a day (afternoon) in most regions where temperate deciduous crops are commercially grown.

All commercial fruit-bearing species use what is known as C_3 photosynthesis (the first carbon compound assimilated in the photosynthetic process has three carbon atoms) (Taiz et al., 2015). Some plant scientists have suggested that the productivity of temperate deciduous fruit trees and vines could be enhanced if they could be converted to the C_4 photosynthetic pathway found in some other plants, such as corn (*Zea mays*). This is highly unlikely, since C_4 photosynthesis would not be as efficient as C_3 photosynthesis in early spring when temperatures are relatively low (Taiz et al., 2015), and there is no competitive advantage of C_4 photosynthesis under the shady conditions (Pearcy & Ehleringer, 1984) that are common within the canopies of most fruit tree and vine species.

1.3 Principles of Photosynthate Distribution and Use

Over the past couple of decades, the concept that carbohydrate partitioning at the whole plant level is primarily driven by growth and development of individual organs has become widely accepted (Gifford & Evans, 1981; Ho, 1988; Lacointe, 2000; Marcelis, 1994; Watson & Casper, 1984; Weinstein & Yanai, 1994). Grossman and DeJong (1995b) used this concept in the development of the PEACH model, and later DeJong (1999) outlined the following four principle steps for applying this concept to logically understand carbon partitioning in fruit trees.

1.3.1 First Principle: A Tree or Vine Is a Collection of Semiautonomous Organs, and Each Organ Has a Genetically Determined, Organ-Specific Developmental Pattern and Growth Potential

Although much emphasis is often placed on considering plants as highly integrated organisms, the concept of semi-autonomy among organs is widely recognized (Harper, 1980; Sprugel et al., 1991; Watson & Casper, 1984; White, 1979). Indeed, the primary morphological features that distinguish one species or cultivar from another are at the organ or sub-organ level (i.e., fruit or leaf shape and size, floral characteristics, etc.), not at the whole plant level. Furthermore, although variation exists, the developmental patterns and growth rates of individual organs under specific environmental conditions are generally predictable. Models have been developed for the growth of fruit (DeJong & Goudriaan, 1989; Genard & Huguet, 1996;

Genard & Souty, 1996; Grossman & DeJong, 1995b; Pavel & DeJong, 1993b; Lakso et al., 1995), shoots and branches (Costes et al., 1993; Costes & Guédon, 1996; Costes et al., 2014; Genard et al., 1998; Grossman & DeJong, 1995c; Lescourret et al., 1998; Johnson & Lakso, 1986), and roots (Bidel et al., 2000). Although pruning and training can drastically alter the shape of trees and vines, they generally have very little effect on individual organ characteristics other than those explained by changes in the local microenvironment of the organs or changes in the availability of carbohydrates due to the proximity of other sinks.

The fact that there appears to be some level of branch autonomy (Sprugel et al., 1991; Heerema et al., 2008) in fruit trees further reinforces this first principle. Branch autonomy tends to functionally isolate some sinks from sources of carbohydrates. When sinks are manipulated through pruning or fruit thinning to create an apparent abundance of photosynthate in one part of the plant and an under-supply somewhere else, the carbon does not freely move to the location of greatest demand. When one scaffold of Y-shaped peach trees was de-fruited, the remaining fruit on the fruited scaffold benefited very little from the carbon that should have been available for fruit growth from the de-fruited scaffold (Marsal et al., 2003). Interestingly, scaffold diameter growth appeared to be one of the sinks that benefited most from the removal of fruit, while root growth was only marginally affected. There is much to be learned about the movement of carbohydrates within the context of whole trees and vines. The role of branch autonomy in early spring, when much of the carbon used for growth is mobilized from storage in the root, trunk, and major branches and is presumably transported in the xylem, is still being elucidated (Zwieniecki et al., 2015).

Carbon partitioning at the branch level has been studied explicitly with radioactive tracer studies (Corelli-Grappadelli et al., 1996) and by manipulating leaf number and fruit load in isolated branches (Genard et al., 1998). Implicit conclusions about carbon partitioning within shoots have also been drawn from fruit thinning studies to determine optimal fruit positioning for fruit size (Marini & Sowers, 1994; Spencer & Couvillon, 1975). These studies support the idea that fruits are strong sinks for carbon within shoots, but their influence on where recently fixed carbon goes varies substantially within the local context of the stem unit.

1.3.2 Second Principle: The Genetic Growth Potential of an Organ Is Activated or Deactivated by Organ-Specific, Endogenous and/or Environmental Signals

The semiautonomous nature of individual organs is further demonstrated by the fact that individual organs on a tree or vine can be experimentally activated by manipulating factors that stimulate the growth of specific organs independently from processes occurring in organs elsewhere on the plant. For instance, exposing individual buds on a branch to rest-breaking treatments can induce bud break in those buds, while similar buds on other parts of a tree remain inactive (Chandler, 1942). Similarly, grafting multiple cultivars with differing chilling requirements onto one trunk will not influence the inherent chilling exposure required for activation by the branch of each specific cultivar. Also, removing the apical meristem on a shoot will promote the activation of growth of lateral buds on the remaining part of the shoot, while buds on other shoots are unaffected (Harris, 1983). Although the exact mechanisms of the environmental and/or endogenous signals that activate growth are not fully understood, the primary site of activation is clearly at the organ or sub-organ level. This is certainly one area where hormones play key roles in influencing carbon partitioning at the whole tree level, as suggested by data on hormone concentration in xylem sap (Sorce et al., 2002).

1.3.3 Third Principle: After an Organ Is Activated, Current Environmental Conditions and Genetic Growth Potential Interact to Determine Conditional Organ Growth Capacity

Although often overlooked, ambient temperature is probably the single most important environmental factor influencing organ growth. Its importance is related to the strong dependence of respiration on temperature. All irreversible plant organ growth is dependent on metabolic activity and enzyme function, and these processes are linked to respiration. Plant respiration generally has a temperature response quotient (Q_{10}) of about 2 (respiration doubles for every 10 °C increase in temperature between 5 and 35 °C, Amthor, 1989). Therefore, the conditional growth capacity of any organ is highly dependent on ambient temperature. The conditional growth capacity of fruits growing under near-optimal field conditions has been modeled for several peach and apple cultivars using mathematical functions responsive to heat accumulation (Berman et al., 1998; DeJong & Goudriaan, 1989; Grossman & DeJong, 1995a; Lakso et al., 1999; Pavel & DeJong, 1993a; Reyes et al., 2016). That other environmental factors such as water status can also have a substantial effect on organ growth is well-documented (Bradford & Hsiao, 1982). Extension growth of shoots has been successfully modeled by considering temperature and dynamic changes in shoot water status (Basile et al., 2003; Berman & DeJong, 1997a). Although fruit growth is generally quite sensitive to water stress, it is important to distinguish between growth in fresh and dry matter since the former is much more sensitive than the latter (Berman & DeJong, 1997b; Girona et al., 1993). Indeed, grape berry growth during the ripening phase (when sugar concentration and dry weight are increasing) is relatively insensitive to mild water deficits (Roby & Matthews, 2004).

Nutrient availability also can strongly influence conditional organ growth capacity because certain nutrients are required as constituents for growing organs.

Accordingly, Saenz et al. (1997) have demonstrated that limited N (nitrogen) availability can increase the developmental rates of peach fruit. Similarly, withholding P (phosphorus) from grapevines has been shown to greatly inhibit reproductive development (Skinner & Matthews, 1989).

It should also be noted that conditional organ growth capacity generally operates as a relative growth rate function. Thus, the conditional organ growth capacity for any future time interval is partially dependent on the realized growth achieved over previous time intervals. This means that if an organ's potential growth is not realized during any preceding time interval due to stress or lack of resources to supply the growth demands of an organ, all subsequent growth is a function of what was achieved previously, and there is no compensatory growth to make up for previously lost growth potential.

1.3.4 Fourth Principle: Actual Organ Growth Is a Consequence of Conditional Organ Growth Capacity, Resource Availability (Assimilate and Nutrient Supply), and Inter-organ Competition for Those Resources

Inter-organ competition for carbohydrates is a function of location relative to sources and sinks of carbohydrates, transport resistances, organ sink efficiency, and organ microenvironment. When conditional growth capacity of an organ is set, organ growth should proceed at a rate equal to the conditional growth capacity as long as transport is not limited and enough resources (carbohydrates) are available to support that organ's growth, as well as the growth of all other competing organs. However, if the tree does not have enough carbohydrates to support the conditional growth capacity of all organs or carbohydrate transport within the tree is limited, then the growth of an individual organ will be a function of its ability to compete for available carbohydrates with other organs. When flowering and pollination occur under favorable conditions, many fruit tree and vine cultivars set very heavy fruit loads. Therefore, lack of available assimilates and inter-fruit competition for carbohydrates are generally the primary factors that limit realized fruit growth in these situations (Keller et al., 2008), and fruit thinning is essential to manage this competition (Cain & Mehlenbacher, 1956; Costa & Vizzoto, 2000; DeJong & Grossman, 1995; Dorsey & McMunn, 1928; Grossman & DeJong, 1995b; Goffinet et al., 1995). Certainly, there are some limitations to carbohydrate transport within trees (DeJong & Grossman, 1995; Marsal et al., 2003), but these are difficult to quantify specifically. There is substantial evidence that fruit growth of many species can compete effectively for carbohydrates with shoot, trunk, and root growth when crop loads are high and all fruits are considered as a collective sink (Grossman & DeJong, 1995a; Marsal et al., 2003; Proebsting, 1958). Yet, there is some evidence to the contrary when pruning stimulates excessive vegetative shoot growth (Grossman & DeJong, 1998). There is also clear documentation of the capacity of individual fruit organs to compete with each other and/or vegetative sinks at the local branch level (Genard et al., 1998). A further complication is that the ability of fruit to compete for carbohydrates appears to vary with the stage of fruit development (DeJong & Grossman, 1995) and location within a tree (Basile et al., 2007).

Upon examining these principles for carbon partitioning in plants, it becomes apparent that phenological patterns of organ growth are the principal determinants of carbon partitioning. When experiments are conducted involving different crop load treatments or some other treatment that dramatically favors the growth of one type of organ over others, biomass data collected at the end of the season appear to indicate that some organs are in direct competition with others (Chalmers & Vanden Ende, 1975; Proebsting, 1958). However, when seasonal patterns of growth are analyzed, it is apparent that direct competition between different organ types is often limited by temporal separation of growth activities (Berman & DeJong, 2003; DeJong et al., 1987; Miller & Walsh, 1988; Rufat & DeJong, 2001). Generally, in late-maturing fruit cultivars and grapes, shoot and root growth is the dominant sink shortly after bud break in the spring. This period is followed by a peak of fruit growth, and then there is a resurgence of root growth (Pace, unpublished data) and shoot diameter growth after harvest (Berman & DeJong, 2003; Grossman & DeJong, 1995a; Williams & Matthews, 1990). It is interesting that breeding efforts to create cultivars with early fruit ripening times have apparently interfered with the natural temporal separation of dominant sink activities in fruit trees. The dominant period of fruit growth of early-maturing peach cultivars often coincides directly with the early peak of shoot growth. This increased competition between fruit and shoot growth results in decreased yield potential (DeJong et al., 1987; Grossman & DeJong, 1995a). There is also some evidence that selection for early-maturing cultivars has involved coincidental selection for decreases in the total fruit growth potential and dry matter content, and these factors account for some of the differences in yield potential between early- and late-maturing cultivars (Berman et al., 1998). Selection for early-maturing fruit has also increased the competition for carbohydrates between sub-organs within the fruit such that seed and endocarp development corresponds with the period of flesh enlargement (Pavel & DeJong, 1993a) as well as increasing the individual fruit relative growth rates so that the tree cannot support as many fruits at one time (Grossman & DeJong, 1995a, b).

1.4 Carbohydrate Storage

Where does "allocation to storage" fit into this scheme of carbon partitioning? Long-term carbohydrate storage is essential for tree and vine survival during adverse conditions (particularly winter for temperate deciduous crops) and subsequent productivity. However, there has been confusion about factors controlling storage reserves in trees (Epron et al., 2012). The prevailing view has been that trees store carbohydrate reserves during times of "excess" photosynthate production (when current supply exceeds demands for growth and tissue metabolism) and deplete reserves when the potential rate of carbohydrate utilization exceeds the rate of current photosynthate production (Oliveira & Priestley, 1988; Kozlowski et al., 1991; Dickson, 1991). This has created the notion that carbohydrate storage occurs only when photosynthates are in excess of demand.

Some researchers have challenged this passive concept of carbohydrate storage arguing that storage reserves are extremely important and storage sinks should not be conceived of as passive reservoirs (Cannell & Dewar, 1994). They have cited examples of control mechanisms for the use of carbohydrate reserves and that storage sinks are refilled at the same time as the growth of other carbohydrate sinks (Weinstein et al., 1991). Indeed, careful evaluation of seasonal dynamics of reserve mobilization and accumulation that correspond to periods of shoot and fruit growth indicates that, although rates of reserve accumulation are generally lower when fruit growth rates are high, reserve accumulation still occurs during this period even though potential fruit growth rates are likely not at a maximum (Ryugo & Davis, 1959; Priestley, 1970). Similarly, although autumn appears to be the main period for accumulation of carbohydrate reserves in temperate deciduous trees, some reserves are accumulated while growth is still occurring during summer (Barbaroux & Bréda, 2002; Landhäusser & Lieffers, 2003; Wong et al., 2003; Winkler & Williams, 1945). Wargo (1979) reported that substantial storage of carbohydrates preceded radial growth of *Acer saccharum* roots and even speculated that root storage of that species may have priority overgrowth for transported carbohydrates.

Da Silva et al. (2014) pointed out that long-term carbohydrate storage in trees is a function of the volume of xylem and phloem parenchyma tissue in the tree. Furthermore, the volume of xylem parenchyma greatly exceeds the volume of phloem parenchyma. Thus, the collective storage "organ" of a tree or vine is the woody parenchyma tissues of the tree. The storage capacity of that "collective organ" is mainly comprised of the overall mass of xylem and phloem parenchyma, the maximum potential concentration of carbohydrates in the xylem and phloem parenchyma, the minimum amount of carbohydrates remaining in the xylem and phloem parenchyma after maximum mobilization, and the relative change in storage activity with xylem aging.

If tree or vine carbohydrate storage capacity is determined primarily as wood is formed, and only current-year sapwood growth can be affected by environmental conditions in a given year, the overall ability for a tree or vine to adjust its storage capacity in response to environmental conditions is very limited. However, this also opens up important questions for future research into the effects of growing conditions on the development of carbohydrate storage capacity in perennial plants, the dynamics of storage and mobilization over time, and the transport of substances from low in the plant to the top at different periods during the season (DeJong, 2016). While most carbohydrate transport is usually thought of as occurring in the phloem, it is clear that much of the upward transport of carbohydrate mobilized from xylem parenchyma in the spring occurs in the xylem (Bonhomme et al., 2010; Ameglio et al., 2002). Tixier et al. (2017) have proposed a novel concept for how carbohydrates stored in lower parts of a tree can be delivered to growing shoot tips in the xylem before there is little or no transpiration to facilitate xylem flow. In addition, while seasonal changes in stored carbohydrates have been known to occur for a long time (Kozlowski et al., 1991), recently it has been shown that diurnal and seasonal changes in temperature patterns cause dynamic changes in starch storage throughout dormancy and facilitate redistribution of storage carbohydrates in response to changes in temperature (Zwieniecki et al., 2015; Sperling et al., 2017). It appears likely that the dynamics of carbohydrate storage in trees may influence tree phenology to a much greater extent than previously recognized (Sperling et al., 2019).

1.5 Fruit Tree Canopy Architecture

1.5.1 Tree Architecture

In recent years, there have been major advances in the understanding of fruit tree architecture. While the growth characteristics of specific fruit tree species and cultivars have been generally recognized for many years, recent advances in statistically based analyses and descriptions of bud fate distributions and shoot and branch growth patterns of multiple species have revealed previously underappreciated similarities and differences in growth characteristics of numerous fruit tree species (Durand et al., 2005; Costes et al., 2006). This has led to a greater understanding that trees are composed of repeating growth units with similarities in patterning of lateral vegetative and floral buds along their axes (Prats-Llinàs et al., 2019) and that patterns at the shoot level lead to differences in fruit bearing at the shoot level and overall tree architecture at the whole tree level (Costes et al., 2014).

These types of statistical analyses of tree architecture have been used to describe differences in growth and architectural development of different apple (Costes & Guedon, 2002; Costes et al., 2003) and almond (*Prunus dulcis*) cultivars (Negron et al., 2013), the influence of dwarfing apple rootstocks on scion growth and flowering (Costes & García-Villanueva, 2007; Seleznyova et al., 2003), and similarities and differences in bud fate structures among rosaceous species (Costes et al., 2014). It also has been used in developing simulation models (Fig. 1.2) to demonstrate canopy growth dynamics in apple (Renton et al., 2006), sweet cherry (*Prunus avium*) (Lang et al., 2004), peach (Lopez et al., 2008; Lescourret et al., 2011), and almond (Lopez et al., 2018), as well as grapevine canopy light interception in response to differential irrigation or fertilization regimes (Iandolino et al., 2013).

1.5.2 Architecture-Informed Pruning

In fruit crops, it is well recognized that there are two objectives with regard to optimizing the capture of solar energy to achieve maximum economic yields: (1) optimizing the total light interception by the canopy and (2) distributing the light within

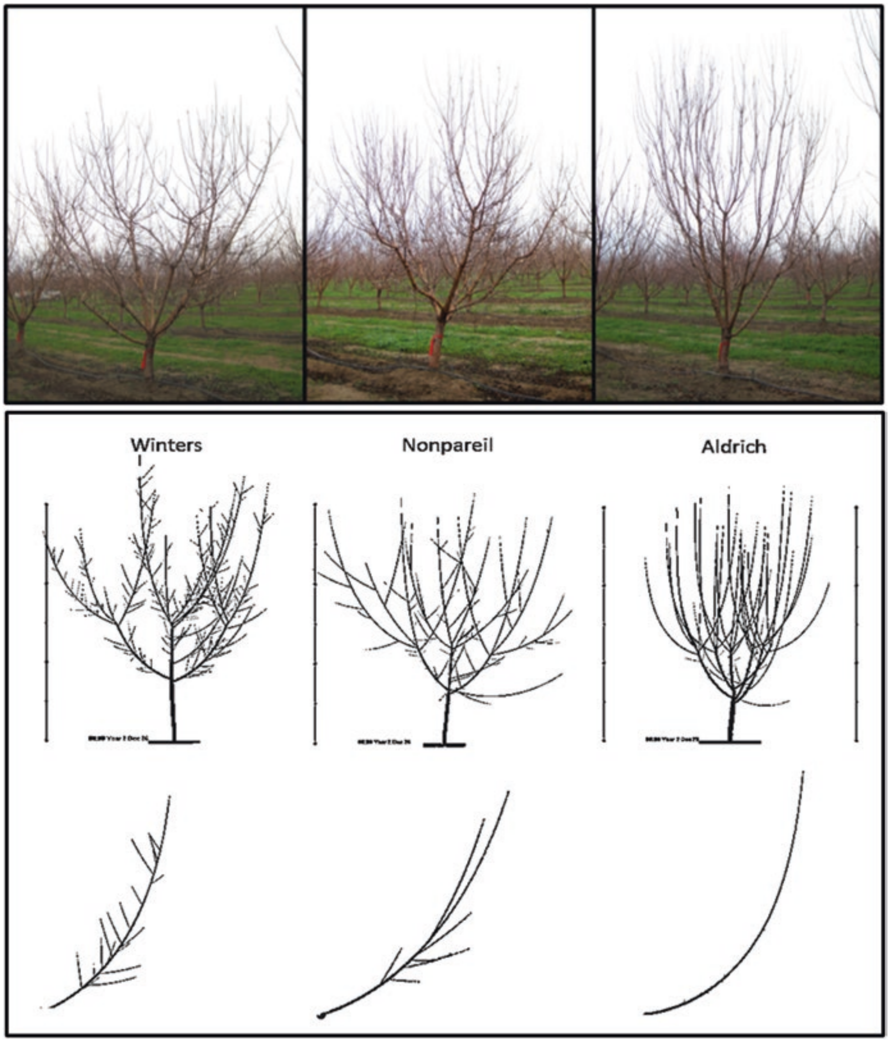

Fig. 1.2 Computer simulations of the tree structures of three almond cultivars resulting from the branching habits of the cultivars (bottom), compared with pictures of trees in the field (top). (From: Lopez et al., 2018)

the canopy to obtain as many high-quality fruit as possible while nurturing high-quality fruiting spurs/shoots for the following year's crop. The increased understanding derived from shoot growth and tree architecture models has been valuable in developing canopy management strategies that optimize pruning procedures that work with the natural growth characteristics of trees to achieve these goals (Costes et al., 2006; Lauri, 2002). This has led to the development of "centrifugal" pruning techniques involving "spur extinction" in apples (Lauri et al., 2004, 2009; Tustin et al., 2011) and less intrusive training systems in stone fruits that adapt pruning practices to the natural growth characteristics of trees (Day et al., 2013; Lang, 2001). Recent research in nut crops, for which concerns about distribution of light within tree canopies to maintain quality are less than for fruit crops but they have been traditionally pruned similarly to fruit crops, has led to the realization that the growth habits and architectures of some nut tree species naturally lend themselves to efficient capture of solar energy. Thus, high yields can be achieved without extensive pruning and training (Tombesi et al., 2011). In California, it is now recommended that young almond and walnut (*Juglans regia*) orchards be managed without traditional, annual pruning (Duncan, 2010; Lampinen et al., 2015).

1.6 Orchard and Vineyard Pests and Diseases

There is a plethora of pests and diseases that can attack or infect tree and vine crops – too many to cover in this short chapter. Leaf-feeding insects and pathogens decrease the effectiveness of the solar energy collection system, while sucking insects and endophytic pathogens can directly feed on photosynthates or inhibit the flow of water, nutrients, and sugars in transport streams. Other insects and pathogens can attack flowers or fruit and directly affect the quantity and quality of harvested fruit. In recent years, there has been an increase in organisms that affect the structure of trees and vines and wood-decaying organisms that decrease the functional life of orchards and vineyards. Finally, insects can vector bacterial and viral diseases that negatively impact water transport, photosynthesis, and carbohydrate partitioning and use.

Other than selecting resistant or tolerant genotypes to plant in orchards or vineyards, the primary defense against most of these insects and pathogens is proper tree and vine care to avoid severe stress or opening up infection sites and the application of pesticides. Increased environmental concerns have also increased the importance of efficient pesticide application reduction of off-target spray drift. All fruit production systems must take these factors into account.

1.7 Concluding Remarks

While it is important to continually increase knowledge and understanding of fundamental aspects of the physiology of fruit trees and vines and there is still much to be learned, it also is important to recognize that researchers have had very little success in improving upon what eons of natural selection has provided in terms of fundamental tree functioning. This should not be a surprise, since trees are solar energy collection systems that have been evolving these systems for millions of years. Most horticultural progress has been achieved through empirical research or using physiological knowledge and understanding to improve tree and orchard management practices, rather than improving physiological processes.

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Chapter 2
Mechanical Management of Modern Planar Fruit Tree Canopies

Long He, Xin Zhang, and Azlan Zahid

Abstract This chapter will discuss the opportunities and challenges of robotic solutions for tree fruit production with modern planar tree canopy management, including the importance of modern tree canopy systems, robot-canopy interaction, robotic system control, in-field sensing for object detection, and three-dimensional (3D) reconstruction. A case study will be presented in robotic branch pruning for apples with modern tree canopies, followed by conclusions and future directions.

2.1 Introduction

2.1.1 Importance of Modern Tree Canopy Management

The US tree fruit industry is an important component of the national agricultural sector, representing ~26% ($11 billion) of all specialty crop production (Perez & Plattner, 2015; USDA-NASS, 2015). The industry is highly labor-intensive and is becoming less sustainable due to rising labor costs and growing labor shortages (Calvin & Martin, 2010; Fennimore & Doohan, 2008). Properly managing the tree canopies with branch training and pruning is an essential task in developing machine-friendly tree architectures, which could greatly benefit the tree fruit industry by adopting new and innovative robotic technologies.

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New tree fruit orchards are increasingly planted in modern, high-density architectures that use dwarfing rootstocks and training systems designed for maximum sunlight interception, higher fruit yields and quality, and easier worker access (Milkovich, 2015; Warrington et al., 1996; Zhang et al., 2015). These new fruit tree training systems and rootstocks could potentially advance and improve the economic benefits of growing highly productive trees with excellent fruit quality (Baugher, 2017; Schupp et al., 2017). The key to maximizing profitability in an orchard operation, however, is the ability to integrate these architectures with mechanized/robotic systems that should perform multiple and diverse tasks. Previous research has indicated that trellis-trained fruiting wall orchards are greatly amenable to robotic/mechanized harvesting (He et al., 2017a, b; Silwal et al., 2016; Zhang et al., 2018a, b) and pruning (Zahid et al., 2020a, b). Some private companies, such as Abundant Robotics, Inc. (founded in 2015) and FFRobotics Ltd. (founded in 2014), are also seeking robotic solutions with these high-density modern planar tree orchards. The well-managed tree canopies would be a core for the successful implementation of mechanical and robotic operations in the orchards.

2.1.2 Conventional Tree Canopy Management

Typically, tree canopy management is done through training and pruning. Training begins at planting and may be required for several years to guide the trees to grow into a specific canopy shape or structure. Pruning is an action of removing branches to control the tree size, fruit quality, and yield, and appropriate pruning can also improve pest and disease control. The operation is generally carried out during winter when the branches are easily visible without leaves (dormant pruning), whereas it sometimes includes summer pruning called hedging. Traditionally, both tree training and pruning are done manually through skilled workers. Figure 2.1a shows tree branch pruning using a long lopper, and Fig. 2.1b shows tying a branch to trellis wire using an electrical tap to form a fruiting wall canopy.

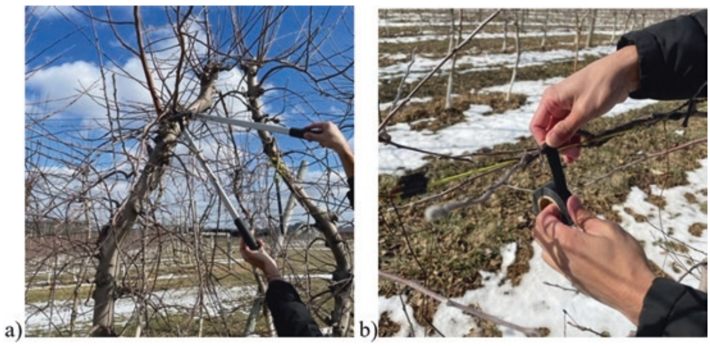

Fig. 2.1 Manual pruning and training for apple tree canopy management. (**a**) Branch pruning using a long lopper and (**b**) canopy training by tying a branch onto trellis wire

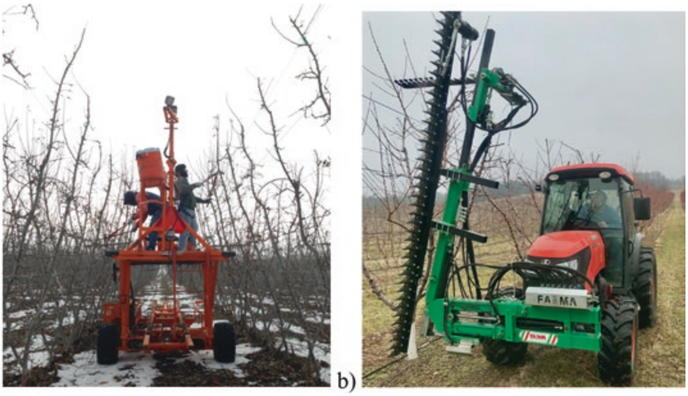

Fig. 2.2 Alternative pruning solutions for tree fruit orchards. (**a**) Pruning assist platform system (Bandit, Automated Ag) and (**b**) mechanical hedging system (FAMA hedger)

Manual canopy management operations are labor-intensive and costly, and the decision varies from person to person based on the skills and experiences of the individual. For pruning, workers make the cutting decision by considering the branch diameter, number, distribution (density), and quality. The availability of farm labor is also becoming an issue for the tree fruit industry. To improve the working efficiency, orchard platforms are used to reduce the time for climbing ladders (Fig. 2.2a). Meanwhile, mechanical hedgers that remove the sides and tops of the canopies have been tested for fruit tree pruning (Fig. 2.2b). The degree of success for hedging is limited by factors such as unwanted vegetative growth, reduced fruit quality, and higher fruit density (Martí & González, 2010; Webster, 1998). Mechanical pruning works well for evergreen fruit-bearing trees like citrus but is found unsuitable for other fruit trees due to complex tree architecture, which requires selective pruning (Childers, 1983). Robotic selective pruning would be a potential solution for these trees.

2.1.3 Tree Fruit Production Mechanization with Modern Tree Canopies

An integrated robotic system for tree fruit production generally includes the robot-canopy interaction for creating a collision-free path for the robot to reach the target, a machine vision system to provide object detection, a manipulator to position the end-effector, and an end-effector to conduct the task (Fig. 2.3). The manipulation of a mechanical system (robotic arm/manipulator) inside the tree canopy to reach the target positions and perform desired tasks, such as a fruit or a branch, is referred to as robot-canopy interaction. For an agricultural robot, environment perception is gathered from a sensing system, followed by the manipulation and control of the

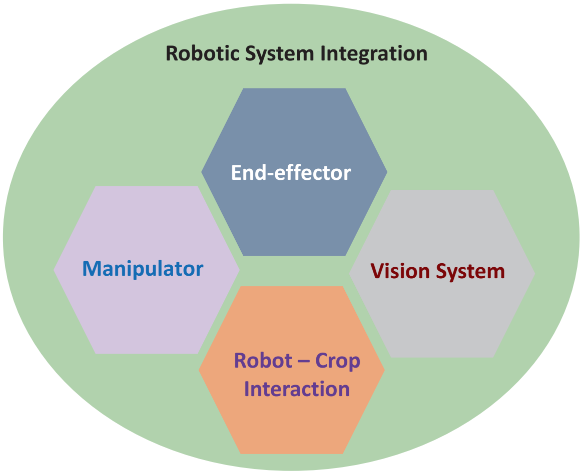

Fig. 2.3 The illustration of an integrated robotic system for tree fruit production

mechanical system to reach the targets. However, the maneuvering of the manipulator in a constrained agriculture workspace poses great challenges. The crucial elements required for superior robot-canopy interactions include kinematic dexterity and spatial requirements of the manipulator, manipulation controls, path planning, and obstacle avoidance. The current research on agricultural manipulators mainly focused on developing fast and efficient machine vision systems for the recognition and localization of the targets. In addition, efforts are underway to improve manipulation controls and optimize path planning and obstacle avoidance. For efficient mechanical or robotic operation, it is important to precisely reconstruct the tree canopy environment and understand the interaction between the canopy and robot, thus developing a collision-free path.

2.2 Robot-Canopy Interaction

2.2.1 Kinematic Dexterity and Spatial Manipulation Requirements

A manipulator/robotic arm is a mechanical system comprising links connected, viz., joints, that perform tasks in one-two-three-dimensional workspaces. The manipulator positions the end-effector close to the target. The last joint of the manipulator is usually connected to an end-effector unit to perform the required task (Kondo et al., 1993). The manipulator is defined in terms of its degrees of freedom (DoFs), link length, link angle, and link offset. Each joint in the manipulator has one DoF, and the kinematic dexterity and spatial requirements are directly related to the number and type of DoFs used in the manipulator assembly (Bac et al., 2017; Burks et al., 2018). The industrial manipulators are well suited to perform repetitive tasks with uniform objects in a free workspace, but agriculture is a complex dynamic environment, and the objects involved vary in shape, size, position, and orientation (Simonton, 1991). Thus, the adoption of robotics for fruit tree canopies has many challenges, which require better assimilation between manipulator abilities and its workspace environment (Kondo & Ting, 1998; Simonton, 1991). For efficient manipulation in an agricultural environment, the manipulators should be designed considering their intended applications, followed by the optimization of the kinematic framework for the said applications (Kondo & Ting, 1998). However, the optimization of manipulator kinematics is challenging due to natural variability between tree architectures and the available workspace for maneuvering. The manipulator could be designed based on various configurations, such as the type of joints and required DoFs, which affect the kinematic dexterity and spatial requirements during manipulation (Bac et al., 2017; Zahid et al., 2020b). Considering the tree canopy environment, the selection of a suitable configuration is critical for efficient robot-canopy interaction.

In the past decade, researchers have developed several manipulators to carry out different operations on tree fruits, such as harvesting (Silwal et al., 2017; Sivaraman, 2006; Zhang & Schueller, 2015) and pruning (Botterill et al., 2017; Zahid et al., 2020b). Considering the total DoF, three-DoF manipulators were the most common choice due to their simple design and control (Harrell et al., 1990). These manipulators could reach the target locations inside the canopy using inverse kinematics, but the orientation of the end-effector tool could not be altered due to low DoFs. The reduced manipulation could result in poor operational performance during robot-canopy interaction, especially when the targets are occluded behind leaves or branches, reducing the manipulator's efficiency. Adding more DoFs, i.e., using a four-DoF manipulator for cherry harvesting (Tanigaki et al., 2008) or a five-DoF manipulator for apple tree pruning (Zahid et al., 2020a), could enhance the manipulator's capabilities to adjust the orientation of the end-effector to some extent. However, the possible orientations of the end-effector tool at any target point in the manipulator workspace are still limited. Considering the constrained workspace inside tree canopies, these low DoF manipulators may not be suitable for harvesting or pruning due to the presence of obstacle branches.

A manipulator with six DoFs (Botterill et al., 2017) could reach positions in Cartesian space (x, y, and z) at any desired angular (yaw, pitch, and roll) components (Corke, 2017). However, for such manipulators, the inverse kinematics result in two poses (elbow up and elbow down) for any desired target position and orientation. This increases the control complexity during collision avoidance, possibly damaging the manipulator, fruit, and/or branches (Burks et al., 2018). For up to six-DoF manipulators, another challenge is their limitation to attain a single pose at any point in the workspace, which could fail to avoid the obstacles (Burks et al., 2018). However, for efficient robot-canopy interaction, ideally, the robot should be able to avoid all obstacles during maneuvering to reach the target fruits and branches. The manipulator with at least one excess DoF, such as seven DoFs (Mehta et al., 2014; Silwal et al., 2016) referred to as redundant manipulators, could be a solution for collision avoidance. These redundant manipulators have an infinite number of poses for any target position in the workspace and could possibly avoid the obstacles by changing the pose to the optimal, presenting a solution for developing manipulators for fruit trees (Burks et al., 2018). However, the additional DoF enhances the kinematic dexterity and manipulability, which are essential to avoid obstacles. But it exponentially increases the manipulation controls' complexity (Choset et al., 2005).

Manipulators for fruit trees could also be categorized based on their types of joints. The performance of the manipulator is influenced by the selection of joint types such as prismatic, revolute, or their combinations. These combinations affect the manipulator's workspace, dexterity, and spatial capabilities during manipulation (Bac et al., 2017). The manipulator should have fewer spatial requirements during manipulation to ensure efficient robotic operation in the complex canopy environment. During maneuvering inside the canopy, each joint contributes to altering the manipulator pose and orientation. The parts of the manipulator that contribute more to its pose change are referred to as the positioning links, and the part that adjusts the orientation of the end-effector tool is referred to as the wrist. With a greater degree of change of pose, the chances for collision with branches increase; thus, the joints for the manipulator positioning links should be selected in ways that result in minimum pose change. Zahid et al. (2020b) developed a manipulator by combining the revolute and prismatic joints for tree pruning. The revolute joints were added directly to the end-effector to reduce the spatial requirements during maneuvering, and the prismatic joints were used for positioning the end-effector to avoid the obstacles. As the low pose change attributes are associated with the prismatic joints, it could be a potential solution for collision avoidance without the need for redundant manipulators. Figure 2.4 shows a few examples of different configurations for a six-DoF manipulator integrated with spherical wrist shear pruner end-effector. The first three joints could be used for the Cartesian positioning (x-, y-, and z-axis) and the last three joints for adjusting the orientation of the end-effector. Each of the shown manipulators has a different workspace (mentioned in the figure caption) and spatial requirements during manipulation inside the canopy. For example, the positioning joints of the Cartesian system, as shown in Fig. 2.4a, may work outside the canopy with a slight pose change and could have decreased spatial capability for maneuvering the end-effector to reach the targets within the tree canopy. Similarly, other joint combinations (Fig. 2.4b–d) could affect the manipulator pose change differently during maneuvering within the tree canopy to reach a target. In addition, the manipulator design should consider the tree features, such as canopy sizes and structures, to reduce the collision potentials with branches.

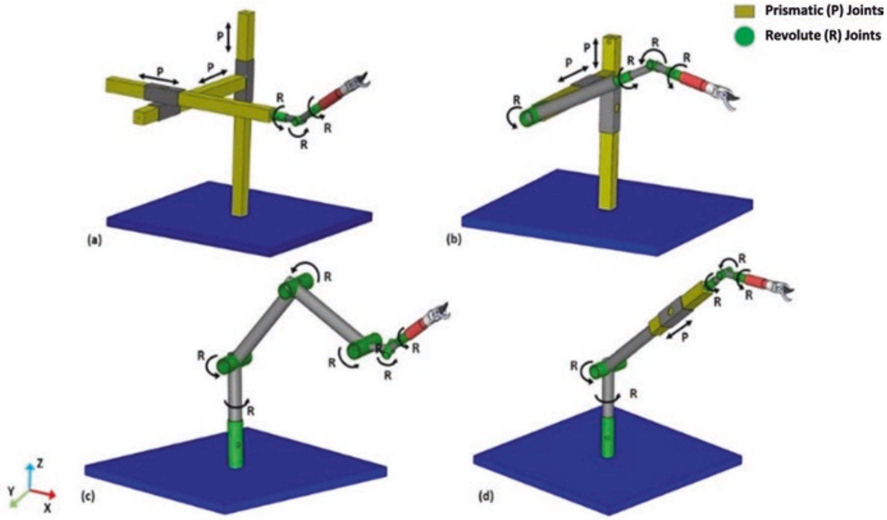

Fig. 2.4 Illustration of a manipulator having different joint configurations integrated with spherical wrist (RRR) end-effector: (**a**) Cartesian (PPP), (**b**) cylindrical (PPR), (**c**) articulated (RRR), and (**d**) spherical (RRP)

2.2.2 Manipulation Controls

The information about the surrounding environment gathered by a sensing system is provided to the manipulator for efficient manipulation control, also referred to as vision-based controls. The visual-based manipulation provides essential information, such as the position and orientation of the target objects and the obstacles. This information is particularly important for the fruit tree operations with variable position and orientation of the targets, such as fruits and branches. The manipulator could use the visual information for manipulation control to accurately reach the target as well as avoid obstacles (Zhao et al., 2016). Any inefficiencies of vision-based control could reduce the performance of the robotic manipulator; thus, they should be given serious attention. The advancement of sensing technologies and control algorithms is leading the way to establishing improved controls for agricultural manipulators.

The vision-based controls are grouped into two classes: global viewing or eye-hand coordination system and visual navigation or visual servo control system (Zhao et al., 2016). In the past, researchers have reportedly used both types of vision-based manipulation controls for agricultural operations. The global viewing system, also referred to as open-loop control, is operated based on a “fixed-point looking followed by moving” scheme. The sensing system scans the entire scene to gather information about the surrounding environment and then starts moving to the target. For open-loop controls, the positioning accuracy depends on the correctness of the information gathered from the sensors, such as cameras, as well as the accuracy of the kinematic model of the manipulator (Yau & Wang, 1996). Botterill et al.

(2017) used an open-loop control scheme to establish the manipulation control for pruning grapevine. Silwal et al. (2017) used an RGB-D camera to establish an open-loop visual control for manipulation to harvest apple trees. The studies reported the accumulation of position and calibration errors due to the inefficiency of the vision system. To achieve higher position accuracy, the open-loop system could be integrated with other sensory information, such as range, proximity, and position sensors, to precisely measure the distance to the target (Zhao et al., 2011; Ringdahl et al., 2019). Han et al. (2012) successfully established the open-loop visual control for manipulation using an RGB stereoscope camera and a laser sensor to measure the distance from the target, with the positing error of less than 1 mm. As there is no position feedback in an open-loop control system, the manipulation efficiency is usually expected to be lower in a dynamic agricultural environment where the targets are under the influence of wind or movement from other reasons, which could change the fruit or branch position.

The second class of vision-based control is the closed-loop or feedback-based control, also referred to as visual servo control (Corke & Hager, 1998). The visual servo control operates the scheme of "simultaneous looking and moving" or "on the fly sensing," making it a completely dynamic system. A sensor-in-hand system provides the on-the-fly information about the position and orientation of the target and the end-effector, which is then used for manipulation control (Hashimoto, 2003). A major advantage of closed-loop control is that the manipulation performance is unaffected by the accuracy of the kinematic model and the calibration of the vision-manipulator system. Harrell et al. (1990) and Mehta and Burks (2014) implemented a visual servo control using a fixed camera for a citrus-harvesting robot, with a position accuracy of 15 mm. However, as the manipulation is solely controlled using the on-the-fly sensor information, the performance depends on the accuracy of the vision system. Zhao et al. (2011) successfully implemented the visual servo controls by using a charge-coupled device (CCD) camera in an eye-in-hand mode for an apple-harvesting robot. You et al. (2020) used an eye-in-hand RGB-D camera configuration to execute visual servo manipulation control for pruning sweet cherry. These studies reported that the depth estimates from the vision system were not always accurate, resulting in lower position accuracy in reaching the targets. In general, visual servo control performs better than open-loop control for different applications; however, it still requires higher target localization accuracy for better manipulation control. Furthermore, as repetitive images are required throughout the operation, the closed-loop control system usually has a higher processing time (Silwal et al., 2017). One key consideration to achieve the desired performance is to match the bandwidth of the controllers with the frame rate of the visual information from the camera sensing system.

A comparison of both types of control is presented in Table 2.1. Both types of visual controls have some advantages and drawbacks; however, the selection for the manipulation control depends on the intended work and the test environment. Additionally, as agriculture is a dynamic and unstructured environment, natural factors, such as wind, should be considered for the selection of a manipulation control scheme. Considering the limitations of both schemes, a combination of open-closed loop could be a possible solution for manipulation control in fruit trees. Font et al.

Table 2.1 A comparison of two types of visual manipulation controls

Visual control	Principle	Advantages	Drawbacks
Open-loop visual control	Hierarchical controlling based on precise 3D positioning	Control is simple; controllability and region of stability are good	High accuracy of vision system required; manipulator and camera calibration required
Closed-loop visual servo control	Dynamic interaction between the manipulator and visual information	No calibration is required; object-friendly; real-time tracking could be achieved	High bandwidth required; local minima of unpredicted camera path

(2014) combined open-loop and visual servo controls in their study. With the open-loop control, the end-effector moved quickly in the proximity of the target, followed by adjusting the position and orientation of the end-effector at the target using on-the-fly guidance from the visual servo.

2.2.3 *Path Planning and Task Sequencing*

The prioritization or sequencing of tasks, such as harvesting fruits or pruning branches following an optimal order, is an important element of robot-canopy interaction. The optimal order could be developed based on various parameters, including minimum rotation of the manipulator's joints, least collision in the workspace, shorter path length, and/or minimal time to reach the target. These optimal sequencing of the robot tasks, also referred to as path or motion sequence planning, are essential to achieve higher performance as well as to ensure the safe operation of the robot during interaction with the canopy (Raja & Pugazhenthi, 2012). In agriculture, the concept of path planning is crucial for successful operation and should be understood based on the types of obstacle environments. Path planning can be categorized into two groups: offline and online path planning (Zhao et al., 2016). Offline path planning requires complete information about the environment before initializing pathfinding, also referred to as global path strategy (commonly referred to as global camera system). For a constrained workspace, where collision avoidance and task sequencing are essential, this approach could be implemented for the static environment (stationary obstacles). On the other hand, online path planning, referred to as local planning, gathers information about the scene as it moves through the environment. In this strategy, pathfinding starts as offline and then switches to online mode during manipulation using the closed-loop feedback system (Zhao et al., 2016). This strategy is useful in the case of dynamic obstacles likely to occur in the agricultural environment.

The most common path-establishing strategy is to reach the target without using any search algorithm (Jia et al., 2020). The kinematic model of the manipulator is used to calculate the displacement toward the target, and the path is established using inverse kinematics based on open-loop control (Yau & Wang, 1996) or visual servo control (Hashimoto, 2003). However, these path strategies did not consider the task sequencing and obstacles in the workspace. Therefore, obstacle avoidance is unlikely. In recent years, with advancements in computing theory, path planning along with task sequencing is becoming more efficient. Researchers have reported numerous task sequencing strategies for different tree fruits. The most common method is to detect and localize the target, followed by the pathfinding and execution for the individual harvest cycle starting from the manipulator's home position (Roldan et al., 2018). Zahid et al. (2020c) implemented a similar individual cycle-based approach for pruning apple tree branches. This single cycle path strategy reduces the performance as the path execution time increases. On the other hand, task planning was also reported by many researchers with harvesting all fruits detected in the scene. Baeten et al. (2008) and Reed et al. (2001) used the all-in-one-cycle-based task planning strategy to reduce cycle time by moving target to target.

In addition to task planning, researchers have also reported different optimization strategies for task sequencing and optimization in tree fruits. For the case of tree fruits, this could be referred to as sequencing pruning cuts, fruit harvesting, or fruit thinning to optimize path length or cycle time. The path minimizing strategy, based on Traveling Salesman Problem (TSP), is widely adopted for optimizing task sequencing (Applegate et al., 2011). Yuan et al. (2009) also implemented a TSP solver by converting the apple harvesting task into a three-dimensional problem to optimize the harvesting sequence. You et al. (2020) implemented a TSP solver for cut point sequencing in pruning sweet cherry and executed the optimal sequence with a high success rate of 92%, with a cycle time of 13 s per branch. Additionally, researchers have presented different amendments to the TSP solver, including Twin-TSP (T-TSP), TSP with Neighborhoods (TSP-N), TSP with Neighborhoods and Duration visits (TSP-ND), and Generalized TSP with Neighborhoods (G-TSP-N), to optimize the manipulator poses, path length, and cycle time. An efficient harvesting sequence plan was implemented by Plebe and Anile (2002) by converting the harvesting task into T-TSP and optimizing it to avoid twin collisions using a self-organizing map model. Jang et al. (2017) developed a TSP-N solver for path sequencing in dynamic obstacle environment, aiming at improving path quality and reduction in the cycle time. These task sequence and optimization strategies could solve the optimal sequence and reduce the cycle time and path length. However, the manipulator collision with branches might still be problematic.

2.2.4 Obstacle Avoidance

The path followed by the manipulator from start to target point without hitting any obstacles is referred to as a collision-free path. In the tree fruit environment, the obstacles are generally the branches and leaves. The manipulation in the presence of obstacles is a great challenge. Path planning and obstacle avoidance should be given attention for successful robotic operation for tree fruits. The term collision avoidance is sometimes interchangeably used with path planning. However, in reality, collision avoidance requires a separate set of considerations for path planning in a constrained environment. The complexity of path planning increased dramatically with the addition of the obstacle detection and avoidance components. In recent years, researchers have gained interest in obstacle detection and avoidance for robot collision-free path planning in the agricultural environment. Obstacle detection is the task performed by the machine vision system, such as camera and proximity and laser sensors. Researchers have integrated obstacle detection sensors with harvesting manipulators, such as a camera for litchi (Cao et al., 2019), a proximity sensor for apple (Zhao et al., 2011), and Light Detection and Ranging (LiDAR) sensor for cherry (Tanigaki et al., 2008). After the detection, the next critical task is to avoid the obstacles while maintaining the manipulator pose required to perform the specified task.

The collision-free path search strategies are categorized into four groups, namely, geometric (grid), probabilistic (random sampling), Artificial Potential Field (APF), and intelligence-based search algorithms (Li et al., 2019). These search algorithms have advantages and drawbacks in terms of path success, search space complexity, processing time, and path optimization (Hwang & Ahuja, 1992; Kaluđer et al., 2011; Kanehara et al., 2007; Yang & Luo, 2004). A performance comparison of different search algorithms is presented in Table 2.2.

Geometric search algorithms are suitable for multi-objective problems, but these algorithms could give satisfactory results with up to two- to three-DoF manipulators (Nash et al., 2009). Probabilistic search approaches are sampling-based algorithms and are among the successful methods (Li et al., 2019). They are less affected by the DoFs of the manipulator but sometimes provide suboptimal solutions (Janson et al., 2017). The Artificial Potential (AP) search works under the influence of attraction and repulsion forces. The potential functions generate attractive forces from the target and repulsive forces from the obstacles (Khatib, 1986). Intelligence search solves multi-objective problems, such as obstacle avoidance with an optimal path using intelligence-based information (Noreen et al., 2016).

Researchers have put forward many strategies for collision-free path planning in the agricultural environment. Van Henten et al. (2003) used the A* search method (Table 2.2) for collision-free path planning of seven-DoF manipulators, but these

Table 2.2 A comparison of different search algorithms

Search algorithm	Description	Limitations
Geometric (A* and D* search)	High success rate. Medium global and local performance	Low performance for high-dimensional dynamic space. Slow processing speed
Probabilistic (rapidly exploring random tree, batch informed tree, etc.)	Fast search speed in high-dimensional space. Low experimental dependence. High global performance	Poor real-time application. Path solution is not always optimal; local minima
Artificial potential (artificial potential field, etc.)	Easy implementation, best suited for a local static environment	Path solution is not always optimal; local minima
Intelligence (genetic algorithm, ant colony, etc.)	High adaptability. Local optimal solution. High convergence speed	Slow processing speed. Poor stability. Inconsistent convergence speed

search methods give satisfactory results for up to three-DoF manipulators (Noreen et al., 2016). For efficient manipulation and collision avoidance, the manipulator should have at least six DoFs. However, with the increase in the DoFs of the manipulator, the computational complexity and search time increase exponentially (Choset et al., 2005). Thus, these search algorithms may not be suitable for robotic operations in a tree fruit environment. Luo et al. (2018) investigated the APF-based search algorithm for collision-free path planning to harvest grapes. These methods resulted in high success, but drawdowns were due to the high processing time as well as non-optimal path solutions.

In recent years, many researchers have investigated probabilistic search algorithms such as rapidly exploring random tree (RRT) and Bi-RRT due to their higher pathfinding success and applicability for multi-DoF (up to 12 DoFs) manipulators (Cao et al., 2019; LaValle, 1998). You et al. (2020) investigated Batch Informed Tree (BIT*) algorithm for pruning grapevines using a six-DoF manipulator and achieved high pathfinding success. The RRT-based search approach is by far the most common strategy for collision-free pathfinding in a tree fruit environment. Botterill et al. (2017) and Zahid et al. (2020c) implemented RRT for the collision-free path planning of grapevine- and apple-pruning robots, respectively. In addition, multiple variants of RRT-based algorithms have also been investigated for robot collision-free path planning in the agricultural environment. Nguyen et al. (2013) implemented an RRT-based collision-free path planning framework to harvest apples using a nine-DoF manipulator. The authors used different algorithms and concluded that the RRT-Connect is the most efficient for path planning in terms of processing time. Cao et al. (2019) also used the RRT algorithm combined with the genetic algorithm (GA) for optimized path planning to harvest litchi. RRT usually has a longer path length due to intrinsic search properties. The RRT search combined with path smoothing and optimization algorithm was implemented by Zahid et al. (2020c) to reduce the path lengths and search time. Bac et al. (2017) implemented Bi-RRT to establish a collision-free path for harvesting sweet pepper in a controlled greenhouse environment. These RRT-based studies reported a high success rate for collision-free path creation in the agricultural environment, with varying processing times. The path planning time depends on the sampling resolution, which should be optimized considering the required path success rate.

2.3 Tree Canopy In-Field Sensing and 3D Reconstruction for Mechanization

2.3.1 In-Field Sensing Technologies

Advanced machine vision systems have been implemented to further develop mechanized equipment for tree fruit production, such as pruning, training, and harvesting, where human inputs are needed throughout each process. There are normally two types of approaches, namely, tree canopy 3D reconstruction and target object identification, depending on the agricultural tasks. Under field light conditions and complex planting patterns, tree canopies need to be reconstructed entirely for some of the mechanized tasks for better canopy characterization, localization, path planning, and geometry measurements. Various technologies have been developed for in-field sensing systems, such as photogrammetry and Light Detection and Ranging (LiDAR).

2.3.1.1 Photogrammetry Imaging for 3D Reconstruction

Utilizing photogrammetry is one of the most effective and affordable methods. One common approach is to use binocular stereo vision systems to reconstruct the target canopy or plant. Ni et al. (2016) developed a stereo vision system with two high-definition (HD) cameras (LifeCam Studio, Microsoft, Redmond, WA, USA) assembled parallelly. For 3D reconstruction, multiple images from different angles and views need to be taken around the target by adopting the Structure-from-Motion (SfM) method. The results showed that the true size of the target could be reconstructed, such as a small lemon tree with leaves. In addition, a time-of-flight-of-light-based (ToF) 3D camera was also often used, where studies have proven that this could reach a more accurate result than stereo vision systems for canopy reconstruction purposes (Beder et al., 2007). Karkee and Adhikari (2015) developed a method for identifying the apple tree trunks and branches for automated pruning using a ToF camera (CamCube 3.0, PMD Technologies, Siegen, Germany), which was mounted on a pan-and-tilt system under the field conditions. With the camera located approximately 1.27 m away from the target trees, all tree trunks and 77% of branches were successfully detected through canopy reconstructions. It was worth noting that all these target trees were young trees interspacing about 0.46 m trained in the tall spindle fruiting wall architectures. Karkee et al. (2014) used the same sensing equipment and tested the pruning results based on the algorithm against the human workers in the field. Results suggested that the root-mean-square deviation (RMSD) was 13% in branch spacing between the workers and the algorithm, which showed promise for algorithm-based automated fruit tree pruning.

Another common option for an affordable and portable camera is using the RGB-Depth (RGB-D) camera. The sensor uses the ToF principle with an infrared laser, a stereo vision system, or a combination of both to acquire depth information. Yang et al. (2019) used an RGB-D sensor, Kinect (Kinect v2, Microsoft, Redmond, WA, USA), for fruit tree 3D reconstruction where the RGB image (1920 × 1080) can be mapped to its depth image (640 × 480) to generate registered 2.5D point cloud data using the ToF principle. Such RGB-D information can provide relatively reliable spatial coordinates of the canopy objects, such as fruits and branches, within a few seconds with much less effort in camera calibration. The results showed an average relative error of 2.5%, 3.6%, and 3.2% with respect to the tree's measurement in height, width, and thickness, individually. In addition to Kinect, RealSense cameras also play an important role as more compact RGB-D cameras in the market with only the need of power consumption from the USB portal, which could potentially benefit the field data collection or near-real-time processing. Dong et al. (2020)

adopted a RealSense RGB-D camera (RealSense R200, Intel, Santa Clara, CA, USA; “R-series” uses stereo vision for computing the depth information) with a hand-held device to map a fruit orchard on a row basis from both sides. By integrating global features and semantic information, both sides of a series of trees can be merged and reconstructed for exploring further canopy characteristics, such as canopy volume, fruit count, and trunk diameter. Unlike “R-series,” “D-series” RealSense cameras utilize infrared light combined with stereo RGB matching to acquire depth information. Such a compact RGB-D camera also can be mounted on an unmanned aerial vehicle (UAV or drone) for faster canopy mapping.

2.3.1.2 LiDAR Imaging for 3D Reconstruction

With the fast development of high-performance computational platforms, Light Detection and Ranging (LiDAR) has offered an alternative method for outdoor canopy 3D reconstructions in addition to conventional ToF sensors. Despite the densely sensed data points and more complex calibration and preprocess steps (Moreno et al., 2020; Wang et al., 2021), LiDAR scanning can offer the most accurate 3D mapping results. Underwood et al. (2016) presented the work using a terrestrial scanning system equipped with LiDAR and other RGB sensors to map flower, canopy volume, and fruit distribution in the almond crop. Individual trees were scanned from both row sides at different times, where the complex internal branch structure and void spaces can be effectively detected by LiDAR mapping. However, there were some misaligned situations for 3D canopy reconstruction due to GPS or localization errors. Such misalignment could significantly affect the calculation of canopy geometry, such as canopy volume (where the voxel size was assumed as 0.001 m^3 and accumulated over a tree), which should be realigned manually (Rosell et al., 2009) or using simultaneous localization and mapping (SLAM) (Cheein & Guivant, 2014). While one of the biggest problems is the occlusions induced by complex branch structures and leaves for ToF sensors, particularly for dense plants where some parts are entirely invisible from the scanner, LiDAR still can provide a certain level of accuracy. Bailey and Ochoa (2018) reconstructed a single dense-foliage tree by integrating the terrestrial LiDAR point cloud data and ray-tracing simulation data (Weber & Penn, 1995), where more than 30,000 leaves were digitally generated and compared. Additionally, some critical canopy parameters at the leaf level were also assessed in this work, such as leaf angle 3D distribution and measurement for biophysical processes. Another work at the leaf level has been completed by Berk et al. (2020), who assessed the leaf area using a terrestrial LiDAR system on 20 apple trees for future precise spraying management. Other than RGB and LiDAR data fusion, Narváez et al. (2016) showed the capability of integrating the thermal imagery and LiDAR data on avocados using portable devices for canopy 3D characterization. Due to the resolution difference between these two data types, all single frames must be registered together to obtain the point cloud data where each point has a temperature value assigned.

Table 2.3 Advantages and limitations of the 3D reconstruction for tree canopy

Advantages
Accurate 3D location of target objects
Occlusions can be much avoided for better path planning
Overall canopy or tree structure can be realized
Limitations
Time-consuming for data collection
Complex camera calibration and preprocessing
Image and point cloud data registration can be challenging
Cost of the equipment can be high, such as LiDAR
Offline or not, real-time processing

The agricultural environment can be complex and unpredictable. With the continued increment in computational performance using advanced hardware and software, precise characterization of tree canopies could be achieved for better facilitating mechanized and automated operations in orchards. 3D canopy reconstruction is one of the most effective ways to provide high-resolution, reliable leaf- or fruit-wise results, where the 3D location should help agricultural robotics with path planning and targets in occlusions, particularly with dense canopies. Some major advantages and disadvantages of reconstructing the entire 3D canopy or tree are summarized in Table 2.3 for comparison.

However, it is worth noting that offline reconstructed perennial trees and canopies can be retrieved later with integration with Real-Time Kinematics-Global Positioning System (RTK-GPS) and Global Navigation Satellite System (GNSS) for further intended tasks, such as precision spraying and pruning, because the main body of the plant can be permanent for at least about 10 years.

2.3.2 *Image Processing Techniques*

Typically, target crop localization, detection (Gongal et al., 2015), and segmentation (Amatya et al., 2017) from agricultural in-field imagery were performed using methods such as morphological operations and color thresholding. However, due to the complex in-field environment and various light conditions, these conventional methods are not sufficient. For example, to make the machine vision system work properly, the operations need to be conducted during nighttime (Amatya et al., 2016), or some other facilitating equipment needs to be installed to reduce the influence of different lighting conditions during the daytime, such as a black background curtain for the over-the-row machine (Gongal et al., 2016). Additionally, the processing speed is relatively slow, given the high resolution of imagery acquired for precise operations.

2.3.2.1 Deep Learning Algorithms

Deep learning-based algorithms, enabled by state-of-the-art AI technologies, started bringing people's attention to image processing tasks about 10 years ago. In the agricultural field, this trend started in 2015. Instead of designing a network from scratch, pre-trained deep learning models (also known as transfer learning) are often used at the beginning by researchers. Pre-trained networks are rich in different characteristics since they were previously trained using thousands of images from public databases, such as ImageNet (Deng et al., 2009) and CIFAR (Krizhevsky & Hinton, 2009). Compared to randomly initializing a network, a pre-trained network may learn better. After considering the three key factors, i.e., accuracy, speed, and size, an appropriate network needs to be utilized and, in most cases, slightly modified for the output layers. Several commonly used networks are AlexNet (Krizhevsky et al., 2012), VGGs (Simonyan and Zisserman, 2014), ResNet (He et al., 2016), DenseNet (Huang et al., 2017), and NASNet (Zoph et al., 2018).

There are two main purposes for using deep learning in image processing: object detection and instance/semantic segmentation in agricultural tasks. Regarding most of the in-field mechanized operations for specialty crops, only one or a few specific types of target objects need to be focused on instead of the entire scene, such as the fruits in fruit harvesting, flowers in blossom thinning, branches in shoot thinning, and leaves in targeted pesticide spraying. Therefore, deep learning-based object detection has been extensively studied (Kamilaris et al., 2018). Zhang et al. (2018a, b) presented the work that deployed a Kinect RGB-D camera and a Region-based Convolutional Neural Network (R-CNN; fine-tuned AlexNet) to detect the segments of apple tree branches. Once all pieces of branch segments have been identified, the detection boxes and depth information have been integrated to predict the trajectory of the branch for automated vibratory apple harvesting in an orchard environment. Similar work has been completed by Majeed et al. (2020), where the segments of the vine cordons were detected and then combined using Faster R-CNN and non-maximal suppression algorithms in cordon trajectory estimation for green shoot thinning during the dense-foliage stage. In addition to one object detection, multiple targets also can be detected at the same time. Zhang et al. (2020) have demonstrated the capability of detecting apples, trunks, and branches using Faster R-CNN with the backbones of AlexNet or VGGs. By extracting different objects' coordinates in the image, the exact vibrating location can be precisely estimated to proceed with the mechanical harvesting of apples. More specifically, once the branches' trajectories have been determined, the apples' locations can provide auxiliary information to decide the grabbing points for the end-effector while not causing any damage to the fruits, with about 73% accuracy achieved. Another similar work can be found by Gao et al. (2020) that a multi-class of fruit conditions (i.e., non-occluded, leaf-occluded, branch−/trellis wire-occluded, and fruit-occluded fruits) were investigated so that the harvesting machine can make better decisions to direct access to collision-free fruits. Another option to understand the entire scene is to conduct image segmentation, for instance, semantic segmentation, where images are classified at the pixel level. This technique was initially used in autonomous vehicle driving (LeCun et al., 2015) and was also applied in some agricultural tasks. Zhang et al. (2021) proposed a method using semantic segmentation to solve the tree trunks and branch identification for automated mass mechanical apple harvesting. Four different classes of pixels were defined as apples, branches, trunks, and leaves. Compared to multi-class object detection, segmentation offers more background information (e.g., leaves) and, more importantly, gives the boundaries of each object. This is particularly useful when the target object has irregular shapes so that a specific path planning should be considered by an agricultural robot to avoid any potential collisions.

2.3.2.2 Improvements in Deep Learning

It was reported that deep learning-based methods overall outperformed conventional image processing methods by tackling agricultural tasks with approximately 41% higher accuracy (Kamilaris et al., 2018). As a result, this method has already become a common practice in handling images with a complex background and lighting conditions, which is highly suitable for agricultural situations as most of the operations are conducted in a field environment. At the same time, researchers are also trying to improve the methodologies using deep neural networks to address the inherent challenges. As we know, introducing imbalanced data into a network can negatively impact the results (Van Hulse et al., 2007). However, this situation is commonly seen in the agricultural field. If the target objects have considerably fewer pixel numbers in an image compared to other objects, such as fruit stems, it would be challenging to train the networks to detect them as most of the pixels belong to the noisy background. One potential way to resolve the problem is to design a regression CNN or RegCNN (Kalampokas et al., 2021). Instead of only assigning each pixel a specific class (i.e., grape stem or non-stem), the distances of other pixels (i.e., non-stem) to the target pixels (i.e., grape stem) were calculated simultaneously. By utilizing regression models in CNNs, continuous values can be predicted to better estimate the stem location. In addition, high-resolution images are normally required in agricultural studies, but many of them suffer from this when feeding those high-resolution images into deep learning networks. Zabawa et al. (2019) presented a reasonable way of splitting large images into small patches and then feeding them into the networks. All small patches were again stitched together afterward. The computational speed can be greatly improved using such a method while preserving the good quality of the fed images. Lastly, it was also noted that most of the deep learning applications in agriculture had involved a dataset augmentation process (Kamilaris et al., 2018), which physically increased the diversity of the imagery dataset, such as image flipping and rotating, and brightness gain multiplier.

Because of the complexity and uncertainty of the uncontrolled agricultural environment, such as field conditions and various lighting conditions, deep learning has been proven highly useful and suitable in this research area. However, unlike some other applications such as autonomous driving which normally have a considerable

Table 2.4 Advantages and limitations of using deep learning algorithms in canopy object detection and segmentation

Advantages
Higher accuracy than conventional methods
Suitable for complex agricultural conditions
Possible of being applied in real time
Performances can be further improved with the fast development of AI-driven industrials
Limitations
Limited dataset and ground-truth annotations
No comprehensive public dataset repository for overall improvement
Time-consuming during the annotation stage
Development depends on the executive platform

number of available datasets from many different resources, agricultural research has always suffered from limited datasets. Additionally, agricultural datasets are challenging to be aggregated due to different sensors and methods used for various research purposes at different precision levels. Therefore, every research team has to annotate tons of the ground-truth labels, which would normally be the most time-consuming step. More importantly, those annotated labels are often used only once and are hard to reuse by other teams. Table 2.4 illustrates several major advantages and limitations of using deep learning applications.

Although there has been a growing community of using 3D scene reconstruction techniques in agriculture over the last few years, the nature of 3D image data compared to 2D image data has certainly brought some constraints, such as the very dense point cloud from LiDAR and long and complex data processing and saving. The superiority of 3D point cloud data is still to be discovered due to the limited availability of resources and tools. Recently, Google Artificial Intelligence (AI) group has released TensorFlow 3D along with the available code library on 3D point cloud data processing (Huang et al., 2020; Najibi et al., 2020), trying to bring state-of-the-art deep learning capabilities to address 3D object detection and 3D semantic/instance segmentation. With such type of efficient tool released, the barriers to deploying a real-time inference system tackling the 3D scene will be reduced for the entire research community.

2.4 Robotic Branch Pruning for Modern Apple Trees (Case Study)

2.4.1 Introduction

Pruning of apple trees is one of the most labor-intensive operations, requiring about 80–120 labor hours per hectare (Mika et al., 2016), accounting for 20% of the total labor costs (Crassweller et al., 2020). Robotic pruning of apple trees is challenging due to the complex tree canopy. The random orientation of the branches makes it difficult for the cutter to reach the desired orientation. Thus, the pruning robot should be designed considering the complex apple tree environment. Many studies have been reported on camera vision systems for 3D canopy reconstruction of apple trees (Karkee et al., 2014; Tabb & Medeiros, 2017). However, no considerable contribution has been reported on the development of a mechanical system, including the manipulator and end-effector for pruning apple trees (He & Schupp, 2018).

The joint configuration of the manipulators should be selected considering the work environment to avoid poor performance. As the joint configurations can change the posture of the robot for a specific task, the configuration of the manipulator should be selected carefully. The end-effector is an integral component of a robotic pruning system, consisting of a tool to perform the pruning cut. Only a few studies have been reported for pruning end-effectors with different cutting mechanisms, such as disk saws and shear blades (Botterill et al., 2017; Zahid et al., 2020a). Considering the complexity of tree canopies, compact robotic cutters are essential for successful operation, and they require appropriate component sizing.

Manipulation in the tree canopy can result in a collision with branches, which reduces the quality of pruning operation (Gongal et al., 2016). Collision-free path planning schemes are widely used for the motion planning of numerous systems such as autonomous vehicles and industrial robotics (Noreen et al., 2016). LaValle (1998) proposed a rapidly exploring random tree (RRT) algorithm for path planning, and it shows high efficiency compared to other available path planning schemes. However, the path solutions of the RRT algorithm are not always smooth and optimal, which results in more computational time and low convergence speed.

Considering the knowledge gap, the primary goal of this study was to develop a robotic manipulation system, including the manipulator and the end-effector for pruning apple trees. Alongside, different collision-free path planning algorithms were developed for the robotic pruning of apple trees. Finally, a series of field tests were conducted on the Fuji apple trees to validate the system performance.

2.4.2 Design of the Robotic Pruning Manipulator System

2.4.2.1 Pruning End-Effector Design

The primary criteria for the end-effector design include the minimum spatial requirement during maneuvering to position the cutter at a specific orientation. The end-effector should reach the target with a specific pose to place the branches within the shear blade opening (Zahid et al., 2020a). Thus, the end-effector should also have high kinematic dexterity to attain multiple poses of the cutter at each point in the workspace. A compact pruning end-effector was designed with the intrinsic three-revolute (3R) degrees of freedom (DoF) configuration (Fig. 2.5). A computer-aided design (CAD) software, SolidWorks (v. 2020, Dassault Systèmes, Vélizy-Villacoublay, France), was used. The design consists of three motors, each offering one revolute DoF to the end-effector. The widely accepted rotation convention, yaw,

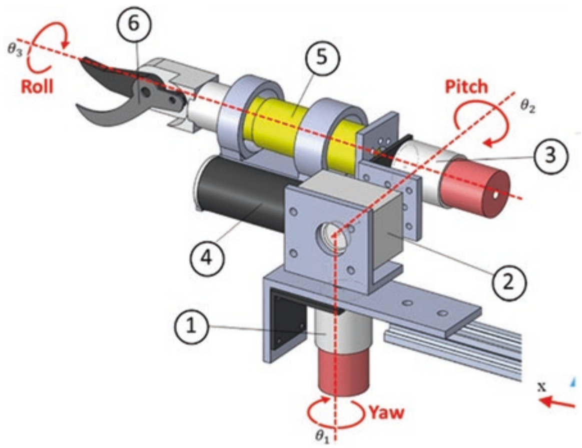

Fig. 2.5 Concept design of the end-effector. (Components: (1) motor for yaw rotation, (2) motor for pitch rotation, (3) motor for roll rotation, (4) self-locking worm gearbox, (5) shear cutter, (6) cutter). (Zahid et al., 2020b)

pitch, and roll (θ_1, θ_2, and θ_3), was used to configure the DoFs of the end-effector. The selection of the cutting mechanism was critical to ensure a successful pruning operation. As efficient pruning requires smooth and split-free cuts, a shear blade was integrated with the end-effector as a cutter tool, attached directly. The maximum rotations for θ_1, θ_2, and θ_3 were 240°, 360°, and 360°, respectively.

2.4.2.2 Integrated Pruning Manipulator Design

The design of the pruning manipulator was a critical task due to the dense apple tree canopy. The key consideration for developing a pruning manipulator was the spatial requirements of the system. During manipulation, the manipulator utilizes a portion of the 3D workspace to change its pose to attain a specific position and orientation of the end-effector cutter. The magnitude of the pose change depends on the DoFs of the manipulator. Thus, it was essential to select the DoFs that offer a minimum pose change. A three-prismatic (3P) DoF system was selected to position the integrated 3R DoF end-effector cutter at target branches due to the low pose change attributes of the Cartesian/linear system. The integrated six (3R3P) DoF robotic pruning system, including a 3P DoF manipulator and 3R DoF end-effector, is shown in Fig. 2.6. The 3P DoF manipulator system was equipped with prismatic joints to move along the x-, y-, and z-axis, respectively. To avoid the dynamic instability and vibration due to the end-effector payload, the system consists of a squared base platform for motion in the x- and y-axes. The pruning end-effector was attached to a linear arm on the z-axis.

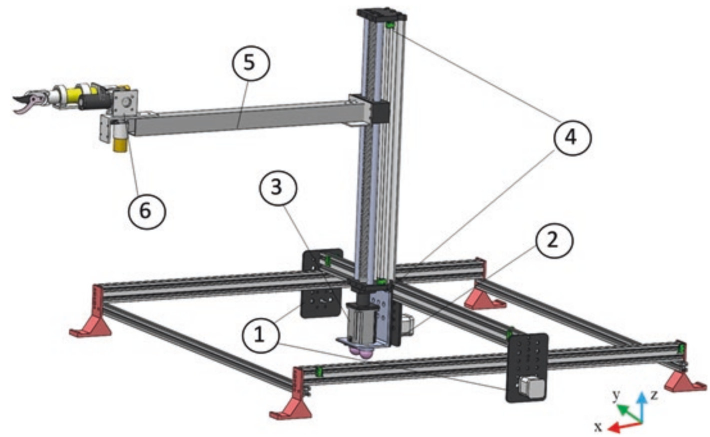

Fig. 2.6 SolidWorks model of the end-effector attached to a Cartesian manipulator; the components include (1) x-axis rails, (2) y-axis rail, (3) z-axis linear actuator, (4) axis limit switches, (5) linear arm, and (6) pruning end-effector. (Zahid et al., 2020b)

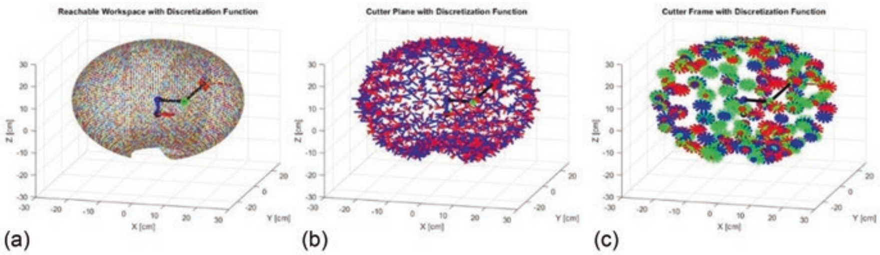

Fig. 2.7 Reachable workspace for the integrated end-effector with (**a**) reachable points, (**b**) cutter plane, and (**c**) cutter frame. (Zahid et al., 2020b)

2.4.2.3 Performance Indices of Robotic Pruner

The kinematic model of the robot was developed by calculating the Denavit-Hartenberg (DH) parameters to simulate the robot performance indices. Details on the robot kinematic model and DH parameters' calculation can be found in the original research article (Zahid et al., 2020b). The forward kinematics of the integrated manipulator was used to calculate different performance indices, including reachable workspace, cutter frame orientations, manipulability, and velocity ellipsoids. The simulations were performed using Matlab (2019a, MathWorks, MA, USA) software to test different performance indices of the robotic pruner.

The simulation results for reachable workspace and cutter frame orientations of the end-effector are shown in Fig. 2.7a–c. The green, blue, and red lines show the 3D cutter frame of the end-effector. The robot workspace analysis indicated that the designed robotic pouring system has a spherical workspace of diameter 240 mm, with a void due to joint limitation. The void space may not affect the robot's

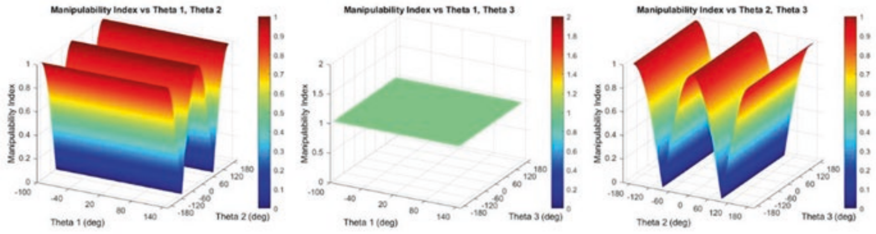

Fig. 2.8 Manipulability index of the integrated pruning end-effector. (Zahid et al., 2020b)

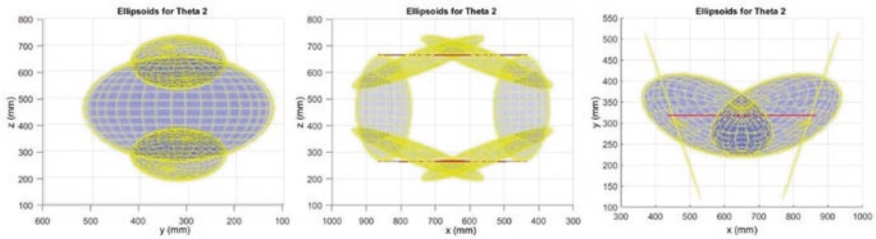

Fig. 2.9 Manipulability ellipsoids with rotation of theta 2 at different coordinate planes. (Zahid et al., 2020b)

performance as it is very unlikely to prune the branches by rotating the cutter backward. Even with this situation, the Cartesian system can move the end-effector backward using the Cartesian positioning system, which will result in positioning the branches on the front side of the cutter. The simulation also indicated that the end-effector could attain a wide orientation of the cutter tool and could reach to cut almost every branch available within the workspace of the robot. The manipulability index was determined to be independent of the rotation of the first and last joint of the end-effector (Fig. 2.8). The result also suggested that the system has only two undesirable configurations of singularity. Based on the velocity ellipsoid simulations (Fig. 2.9), it was found that these singularity configurations could occur when the cutter is pointing vertically up or down (red lines), a very unlikely scenario to cut the branches.

2.4.3 Collision-Free Path Planning for Robotic Pruning

2.4.3.1 Reconstruction of Apple Trees

The 3D model of an apple tree was required to create collision-free paths. The data collection system consisted of a 3D laser scanner (VLP-16, Velodyne LiDAR, San Jose, CA, USA) and a laptop computer (Dell, Round Rock, TX, USA). The 3D point cloud data were preprocessed using Matlab software. Through the

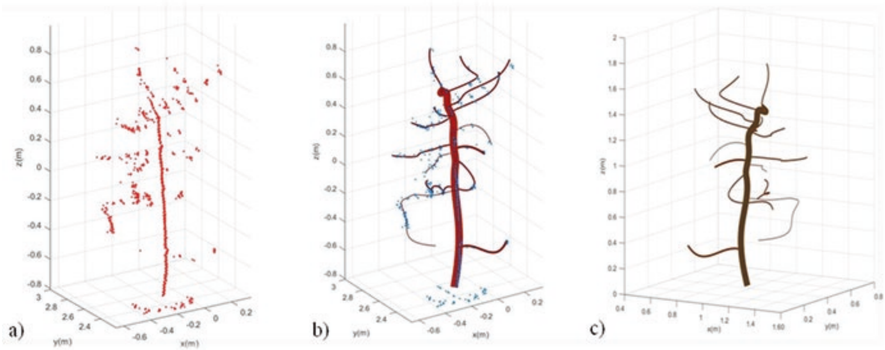

Fig. 2.10 (**a**) Point cloud data from the LiDAR sensor. (**b**) Segmented tree trunk and primary branches. (**c**) A view of a 3D reconstructed apple tree

preprocessing, the point cloud image of the apple tree was established (Fig. 2.10a). A point cloud algorithm was used for the segmentation of branches and tree trunks (Fig. 2.10b). A few small branches were missed in the LiDAR scanner due to the limitation of sensor resolution. However, those small branches were not considered potential obstacles and were ignored for the 3D reconstruction. For connecting the point clouds of the trunk and branches, the *Spline()* function was used (Fig. 2.10c).

2.4.3.2 Path Planning Algorithms and Simulation

An obstacle avoidance algorithm using a rapidly exploring random tree (RRT) search was implemented for a collision-free path to reach the target pruning points. The RRT algorithm performs two checks: manipulator collision and end-effector path collision. The target branch and pruning cut point coordinates were added to the algorithm to start the pathfinding. If the RRT search nodes exist in collision-free space, the specific path nodes are added to the final solution, and the process continues until the connected nodes reach the target location. Furthermore, RRT path smoothing and optimization algorithms were also developed to improve path planning. The RRT smoothing aimed to reduce the path length by removing unnecessary path nodes. For path optimization, a nonlinear optimization algorithm was implemented with initial and boundary conditions. The minimum avoidance distance from the obstacles was set to 60 mm.

The path planning was performed in a simulation environment to reach different target pruning points (Fig. 2.11). The coordinates of target pruning points on each branch were marked 20 mm away from the tree trunk. The path planning algorithms were successfully implemented to reach target branches at different orientations' cutter as defined in the algorithms. The RRT algorithm was successful in finding a collision-free path (red line path) for defined pruning points within the virtual tree environment (Fig. 2.11). The smoothing and optimizing methods successfully reduced the RRT path lengths (green line path) for all target branches by removing

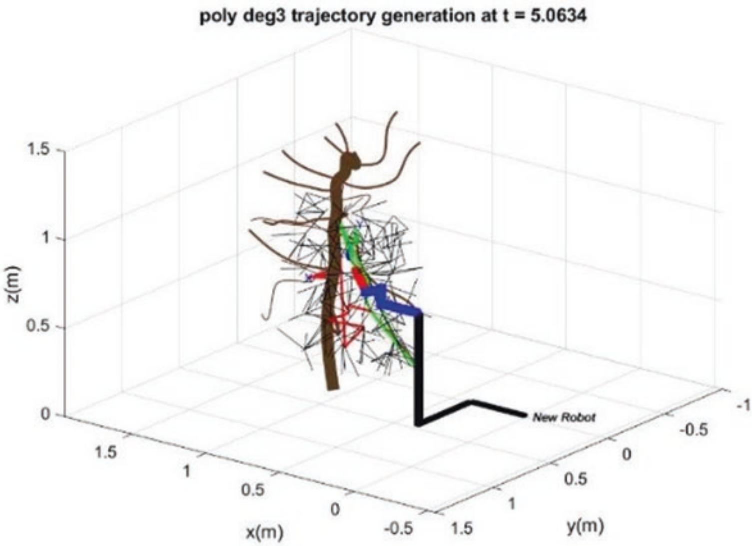

Fig. 2.11 Collision-free path planning using a 3R3P DoF robotic pruning manipulator

the redundant nodes in the original path. The mean computational time was 14 s per branch. The path planning time depends on the number of collision checks required to establish a collision-free path. As the Cartesian motion (3P) occurred outside the tree canopy, the collision check was performed only for the rotational part of the robotic pruner (3R DoF end-effector) and the linear arm (position the end-effector inside the canopy), thus reducing the overall computational time for creating the path.

2.4.4 Prototype Development and Field Tests

The prototype of the integrated robotic pruner was developed at Penn State's Fruit Research and Extension Center, Biglerville, Pennsylvania (Fig. 2.12). A set of three DC geared motors was used for the 3R end-effector. A modified DC motor-powered shear pruner, coupled with a gearbox, was attached as an end-effector cutting tool. Two NEMA-17 stepper motors were used for establishing the Cartesian motion along the x- and y-axes. To covert the rotational to linear motion, the belt and pulley mechanisms were attached to the motor shafts. As the z-axis has to carry the linear arm and the end-effector payload, a NEMA-34-driven lead-screw actuator was used. For field tests, an Arduino-based control system was developed to control the movement of the integrated robotic pruning system.

The field tests were conducted on Fuji apple trees trained to fruiting wall architecture. In total, 100 cuts were applied on branches at a wide array of orientation ranges. The cuts were applied at 20 mm from the tree trunk to evaluate the end-effector cutter's capability to prune the branches close to the trunk. For each

Fig. 2.12 Experimental setup of the integrated pruning system in a Fuji apple orchard. (Zahid et al., 2020b)

successful cut, the branch diameter and the robot's joint angles were recorded. The field tests validated the design parameters of the integrated pruning system. The field tests validated the design parameters and all simulation results. During the test, it was observed that the cutter could collide with the trunk when the target point was close to the trunk, and only the perpendicular cutting posture was considered. The chance of missing the target branch increased when the cutter plane and branch axis were not perpendicular, as the effective cutter opening for the branch entrance was reduced. The developed cutter was able to reach all targeted branches and cut up to 25-mm-diameter branches. With this cutting capability, the developed robotic system is suitable to use in the modern apple tree architecture.

2.5 Conclusion and Future Directions

As we discussed earlier, tree structures in the modern orchard are getting much simpler by adopting the intensive planar training system. The simpler canopies provide opportunities for implementing mechanical and robotic solutions for the in-field tasks of tree fruit production. An accurate, robust, fast, or inexpensive system would be considered a successful robotic system. However, even with modern trees, these in-field tasks can still be challenging due to the nature of the biological system, especially the interaction between the tree canopy and the robotic systems. For example, with robotic pruning, the cuts on branches require high precision with a cutting end-effector, applied at the right locations and perpendicular to branch orientation. This chapter reviewed and analyzed the core technologies for the robotic solutions for modern tree orchards, including robot-canopy interaction, in-field sensing, collision-free path calculation, and manipulation control.

Regarding in-field sensing, although canopy reconstruction may provide more in-depth 3D information for any in-field mechanized operations, the speed and computation constraints have limited its current usage. During the last few years, proximal in-field sensing technologies and processing techniques have been greatly advanced with the prosperously developed AI-driven disciplinaries. Deep learning-based techniques have gradually become the common practice for image processing (LeCun et al., 2015), which is the critical first step for orchard automation and mechanization. As a continuously growing community becomes more interested in utilizing AI-enabled deep learning techniques in agricultural research, the future directions include (1) further improvement of deep learning networks' architectures, such as adding attention mechanism module (Fu et al., 2019), using regional dropout method (DeVries & Taylor, 2017), and adding gradient noises (Neelakantan et al., 2015); (2) utilizing generative adversarial networks (GANs; Goodfellow et al., 2014) to address the main issue of the limited number of agricultural images and annotations; and (3) further developing semi−/self-supervised deep learning techniques (Ji et al., 2019; Wu & Prasad, 2017) that require much less or no manual annotations. Although this is a highly promising research direction, some major concerns were also presented. For example, most of the researchers are still paying too much attention to sensing technologies themselves only, rather than implementing the technologies into actual mechanized orchard operations or canopy management. In addition, onboard computing with embedded systems (e.g., NVIDIA Jetson TX2 module) will be highly necessary for utilizing such deep learning-driven techniques in real orchard scenarios.

The accessibility of the robotic manipulator and end-effector is challenging due to the complexity and variability of the agricultural environment, as well as the required speed of operation. The previously developed pruning robots were typically using serial robotic arms, while this level of specificity in the spatial placement of the end-effector results in a complex set of maneuvers and slows the pruning process. Meanwhile, a serial robot arm with an end-effector requires a large space for the cutter to engage with the branches. Although it is not for pruning directly, the effort has been made to simplify the maneuvers and improve the efficiency of robotic operations in harvesting. Two robotic fruit-picking robots have been developed and tested; as mentioned earlier, one is from FFRobotics (Gesher HaEts 12, Bnei Dror, Israel), and the other one is from Abundant Robotics (Abundant Robotics, California, CA, USA). Similar robotic arms could be considered for developing pruning systems. However, these arms did not need to achieve specific orientations to pick fruits. For robotic pruning, the end-effector (cutter) needs not only to reach the right location but also to be placed perpendicularly to the branch. To be always perpendicular to the branch as well as using the parallel type of robotic arm, the end-effector should be with adjustable orientation. With this kind of end-effector, the cutter itself could be rotated with very small spatial effort. Moreover, the cutter could be made of a saw blade with no specific orientation constraints.

Finally, the economics of the robotic pruning system also needs to be considered. Typically, the cost of a robotic system is high. The use of off-the-shelf robotic arms (such as Robolink, Igus) and low-cost sensing system (such as Kinect v2, Microsoft) could decrease the overall cost of robotic systems. Therefore, with the consideration of the labor shortage issue as well as putting effort into building low-cost robotic pruning systems with off-the-shelf components, the benefit of developing a robotic pruning system would be obvious. Meanwhile, multiple robots could be employed to improve working efficiency. The cost/benefit ratio of a robotic system will have to be analyzed after the machine is built.

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Chapter 3
Orchard Water Management

Isaya Kisekka

Abstract Many world regions with large commercial fruit or nut production are experiencing constrained water supplies due to increased competition from other beneficial uses, government policies, and climate change. There is an urgent need to develop smart irrigation solutions to help growers remain profitable and environmentally sustainable. We reviewed the latest advances in orchard irrigation systems, including zone irrigation management, variable rate irrigation, and scheduling technologies. Smart irrigation scheduling in orchards applies the right amount of water at the right time and in the right place. The ideal orchard water management strategy should combine ETa-based monitoring with stem water potential and soil water monitoring. One of the significant advances in technology has been automated stem water potential monitoring. To reduce orchard water use without negatively impacting economic returns, growers need well-designed, well-operated, and well-maintained irrigation systems that achieve high distribution uniformity and application efficiencies. In addition, growers will need to implement deficit irrigation strategies informed by knowledge of the sensitivity of the different growth stages to water stress. Soil health practices such as residue management can also reduce soil evaporation and improve soil water holding capacity. The concepts and management practices discussed in this chapter, while focused on almonds, apply to other types of orchards, e.g., pistachios, walnuts, or fruit orchards.

3.1 Introduction

Product quality is not trivial when optimizing orchard water management to minimize spatial variability in canopy development and yield to maximize water use efficiency (WUE). Many arid regions (e.g., California, Israel, Chile, and Australia) with sizeable commercial fruit or nut production are experiencing constrained water

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supplies due to increased competition from other beneficial uses, government policies, and climate change. There is an urgent need to develop smart irrigation solutions to help growers remain profitable and environmentally sustainable. Smart irrigation management involves combining flexible, well-designed, and well-maintained irrigation systems with integrated sensing of water status in the soil-plant-atmosphere system to refine irrigation scheduling decisions to meet production goals. Smart irrigation, also known as site-specific irrigation, aims to guide decisions about when to initiate irrigation, how much water to apply, and where. While the concepts discussed in this chapter can apply to other woody perennial orchards, we will use almond orchards as an example to discuss recent advances in orchard irrigation systems and water management.

3.2 Advances in Almond Orchard Irrigation Systems

3.2.1 Zone Irrigation Management (ZIM) and Variable Rate Irrigation (VRI)

Under zone irrigation management (ZIM), the farm is divided into manageable zones based on soils with similar infiltration rates, water holding capacity, and soil fertility and salinity characteristics. In the case of existing irrigation systems, they are retrofitted with automated or manual control valves and used to irrigate zones with similar soils together. This is a more simplistic attempt to manage spatial variability than variable rate irrigation (VRI). This improves the grower's adoption potential by avoiding the cost of re-investing in a completely new irrigation system. While ZIM might not be the solution to manage spatial variability for all growers, it provides a low-cost option for increasing flexibility in irrigation scheduling. Figure 3.1 shows a farm in the Sacramento Valley of California that has implemented ZIM to manage differences in soil infiltration and soil water holding capacity between heavy clay, loam, and gravel loam soil zones.

VRI in almond orchards begins with a delineation of irrigation management zones. This process involves mapping the soil to understand underlying heterogeneity. Fulton et al. (2011) describe the use of proximal digital soil mapping to determine VRI zones in almond orchards. In the case of established orchards, spatial variability in light interception can also be used in the delineation of VRI zones. Unlike ZIM, VRI zones are usually irregular in shape, following the major factor driving the variability pattern. VRI tends to cost more to implement than ZIM because more materials are needed. For example, a variable frequency drive (VFD) is required to manage flow and pressure to zones of different sizes. Kizer et al. (2018) reported that VRI in almonds improved nut yields. It is worth noting that without automation, ZIM and VRI irrigation scheduling can get very complicated and can result in unintended errors in irrigation scheduling as it becomes too complicated to keep track of which zone has been irrigated and which ones haven't. Automation is recommended to realize positive results from ZIM and VRI.

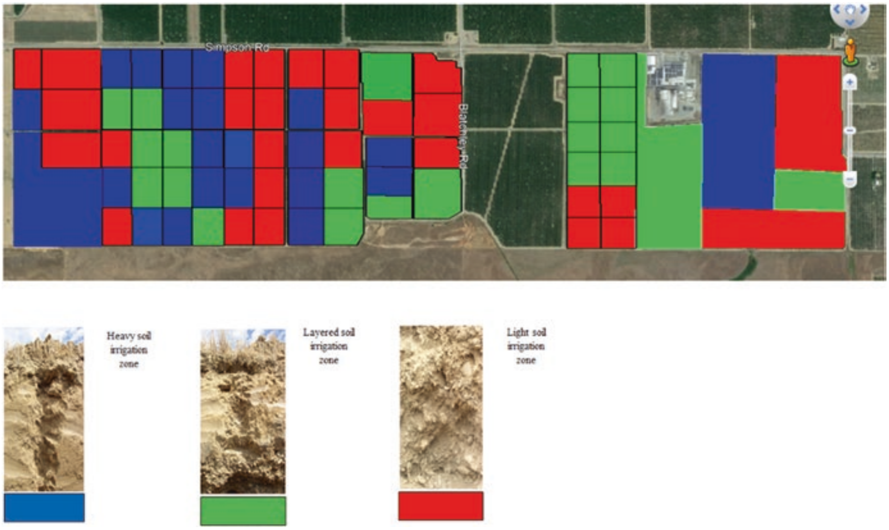

Fig. 3.1 Irrigation zones at the Esteve Ranch near Corning, California. Zones with the same color are irrigated in the same irrigation set to manage differences in soil physical and hydraulic properties. Blue corresponds to heavy clay soil zones, green to layered soil zones, and red to gravely loam soil zones

3.2.2 Automation of Orchard Smart Irrigation Systems

Almond growers can improve profitability and enhance WUE by adopting smart irrigation technologies. Smart irrigation can be autonomous or manual, depending on water supply and irrigation system design. Autonomous smart irrigation can reduce labor costs and minimize human error in the implementation of irrigation schedules. Recent advances in remote automated valve actuation (i.e., remotely controlled opening and closing of valves) are critical to the successful implementation of irrigation scheduling. Examples of commercially available remote valve control solutions for orchards include Vinduino wireless valve controller (https://vinduino.com/) and Bermad Smart Irrigation Solenoid Controller (https://www.bermad.com/product/greenapp-2/) among others. In addition, some of the remote valve control systems allow growers to remotely monitor water flow meters or system pressure in the irrigation lines. The ability to monitor flow and pressure in each irrigation zone provides a powerful tool for evaluating the system's hydraulic performance. For example, if the system is operating at a flow rate higher than the design flow rate, there is probably a leak in the system that requires inspection. On the other hand, if the system is operating at a much higher pressure than the design pressure, the emitters are probably clogged, and the system needs to be flushed. Also, technology exists to automate various components of the head control, including backflushing for the filtration system, fertigation, and VFDs to optimize pump performance. There is a need to integrate these systems into a unified framework capable of seamlessly functioning in an autonomous or semi-autonomous fashion to fully realize the benefits of automation irrigation in terms of optimized production, lower labor costs, and better environmental outcomes.

3.2.3 New Approaches to Assessing Orchard Irrigation System Performance

For example, irrigation system performance is typically evaluated using distribution uniformity (DU) in almond orchards. DU refers to how uniformly water is applied in a given irrigation zone or block and is mathematically expressed as the ratio of the average flow of the lowest 25% emitters measured divided by the average flow of all emitters measured. Growers can conduct a DU test on their own or hire a professional irrigation technician to conduct the test. In California, DU tests are conducted by resource conservation districts (the extension arm of the California Department of Conservation), private consultants, or universities. However, this traditional approach to the evaluation of irrigation systems is laborious and time-consuming; therefore, most growers do not conduct this important part of good irrigation management, especially on large farms. However, new remote sensing-based approaches are being developed to provide proxy feedback on irrigation system performance, e.g., the transpiration uniformity (TU) shown in Fig. 3.2. The TU is an expression of cumulative thermal stress anomalies over several aerial flights

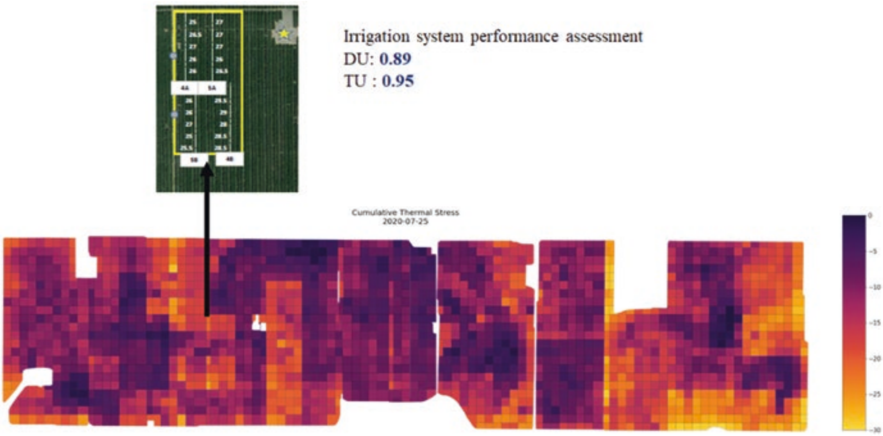

Fig. 3.2 Transpiration uniformity (TU) in almond and walnut orchards estimated from aerial remote sensing thermal imagery (Ceres Imaging Inc., Oakland, California) representing cumulative temperature anomalies on a 64 m pixel grid. The dark purple pixels represent low stress (~0), and the bright yellow pixels show high stress. On top, traditional distribution uniformity (DU) was estimated from emitter flow rates measured in catch cans in an almond orchard block at the Esteve Ranch near Corning, California

(i.e., the difference in the radiometric temperature between the coolest pixel in the image and the rest of the pixels). Field evaluation of DU and TU showed good agreement. It is worth noting that DU and TU measure different properties; the former measures water application uniformity, while the latter measures water use. TU has the advantage that it can be scaled over large areas and is cheaper to conduct frequently.

3.3 Orchard Crop Water Use

Orchard crop water use is influenced by the type of crop being grown. For example, irrigation water requirements in almond orchards are influenced by two main factors, i.e., the orchard evapotranspiration (ETa) and the irrigation system efficiency (IE). IE is the ratio of beneficial uses (e.g., ETa, frost protection, leaching for salinity management, etc.) to non-beneficial uses (e.g., weed ET, wind drift from sprinklers, evaporation from soil and canals, deep percolation, and runoff) of applied water (Steduto et al., 2012). However, depending on the purpose and scale of assessment, some of the non-beneficial uses could be considered beneficial, e.g., deep percolation that ends up as groundwater recharge. IE can be expressed as application efficiency (AE) or the proportion of the applied water available for crop use. For example, in California, where more than 80% of the almond growers have shifted from flood to micro-irrigation, application efficiencies have significantly improved, resulting in more than 30% reduction in applied water over the last three decades, as reported in the Almond Board of California CASP grower surveys. However, DU remains a major factor affecting orchard irrigation efficiency and is significantly influenced by irrigation system design, operation, and maintenance. Even the best micro-irrigation system, if poorly maintained, can develop low DU that affects orchard canopy growth and uniformity.

In an orchard with well-operated and well-maintained micro-irrigation systems, almond ETa is the main factor driving orchard irrigation water requirements. In California, seasonal almond ETa ranges from 1041–1117 mm in the Sacramento Valley to 1270–1372 mm in the southern San Joaquin Valley (Fulton et al., 2001). There is a need to determine almond ET at different growth stages (i.e., young versus mature orchards), cultural practices (e.g., cover crop versus no cover crops), and environmental factors (e.g., salinity and sodic conditions). A significant amount of research has been done in California to estimate almond ET under these various conditions (Goldhamer et al., 2006; Sanden et al., 2012; Spinelli et al., 2016; Bellvert et al., 2018; Xue et al., 2020; Peddinti & Kisekka, 2021; Drechsler et al., 2021). Most of the earlier work focused on developing crop coefficients that could be used with reference ET (ETo) to determine orchard crop water use. In contrast, recent work focuses on estimating site-specific almond ETa from remote sensing. After the net irrigation requirement is determined, the next step is to develop an optimum smart irrigation schedule.

3.4 Smart Irrigation Scheduling

Smart irrigation scheduling involves developing a procedure for supplying the trees with the right amount of water at the right time and in the right place. Traditional irrigation prioritized determining the right amount and timing, but smart irrigation introduces the spatial aspect. Irrigation scheduling aims to maximize net economic returns for a given orchard while enhancing water stewardship. Many almond growers still irrigate based on their practical experience, irrigation system limitations, and water supply constraints, e.g., irrigation district water deliveries or diminished well capacities. An Almond Board of California CASP survey (Table 3.1) shows the criteria on which growers base their irrigation scheduling decisions. Scientific research over the last several decades has developed three primary methods of irrigation scheduling in orchards: (1) soil water monitoring, (2) plant water status monitoring, and (3) ET-based soil water budgets. However, as shown in Table 3.1, most growers still use the traditional hand feel method to schedule irrigation. New technologies that are easier to use might improve adoption levels of scientifically based irrigation scheduling.

3.4.1 Soil Water Monitoring

Smart irrigation scheduling based on soil water sensing involves monitoring soil water content in the root zone at two or more locations until a threshold set a priori is reached and irrigation water is replenished. When soil probes (capable of monitoring soil water at multiple depths) are used, the sensor can be used to determine the direction of soil water movement instead of setting a soil water threshold or trigger. This information is used to determine when to end an irrigation set. Soil water sensors can also track root water uptake dynamics characterized by sharp declines in water content during the day and negligible changes in soil water at night (Fig. 3.3). Examples of commercially available soil water sensors include water potential sensors, resistivity-based sensors (e.g., gypsum block), time-domain reflectometry sensors (TDR), and frequency-domain reflectometry sensors (FDR).

Table 3.1 Irrigation scheduling methods used by almond growers in California. Data is collected as part of the California Almond Sustainability Program (CASP) survey conducted by the Almond Board of California

Irrigation scheduling method	Percentage of adoption (%)
Hand feel method used to determine moisture	89
ETc-based scheduling	75
Soil moisture sensors	61
Use of flow meters	43
Stem water potential using pressure chamber	31
Water district-influenced schedule	23

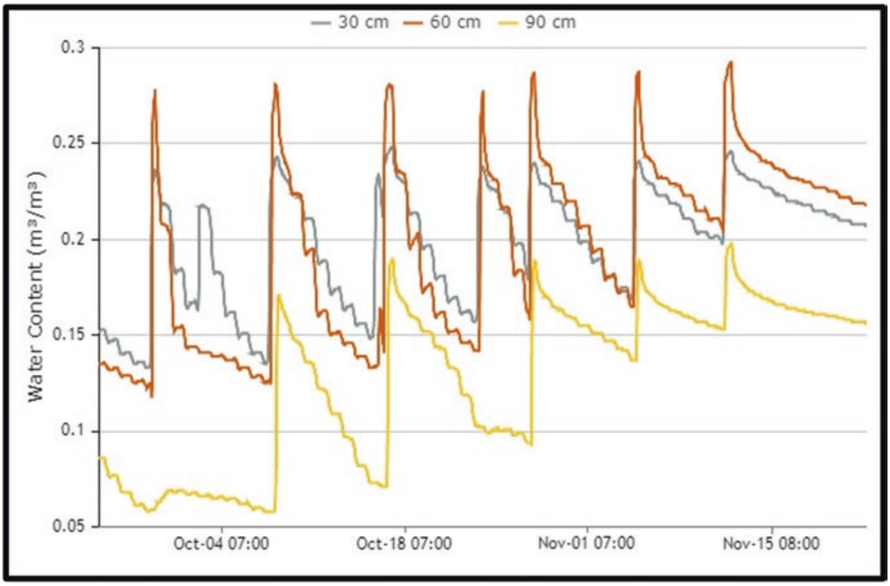

Fig. 3.3 Root zone soil water dynamics during the post-harvest period at three depths in an almond orchard near Arbuckle, California. The effect of root zone water uptake is clearly shown by the jagged pattern in the graphs at different depths. The spikes represent irrigation events

Neutron probes and heat dissipation sensors are primarily used in research. The reader is referred to a detailed description of how these different sensors operate (Evett, 2008). While the science behind how these different sensors operate has not changed for decades, there has been a significant improvement in the electronics and data communication protocols, resulting in lower costs and seamless real-time monitoring. It is worth noting that no soil water sensor currently exists that can measure soil water directly; they all measure a surrogate property, e.g., the dielectric constant that is correlated to soil water content. If accurate soil water content measurements are required, site-specific calibration for each sensor has to be done. Another disadvantage of most commercially available sensors is that they sense a very small soil volume, which results in variability between sensor replicates making interpretation very difficult for the growers. Most growers use the soil water sensor data to qualitatively assess trends in soil water dynamics but not to determine actual soil water content. As shown in Table 3.1, many almond growers have adopted soil moisture sensors. However, there is still a challenge associated with deciding where to install the sensors and how many you need to characterize soil water content in an orchard.

New advanced soil water monitoring using cosmic-ray neutron probe (CRNP) appears promising for soil water monitoring at orchard scales. CRNP detects fast moving neutrons in the soil and in the air just above the soil. The neutron intensity is then correlated to soil water (Benzinger & Jawerth, 2018). Research comparing the CRNP to an in situ neutron probe in an almond orchard has shown very good

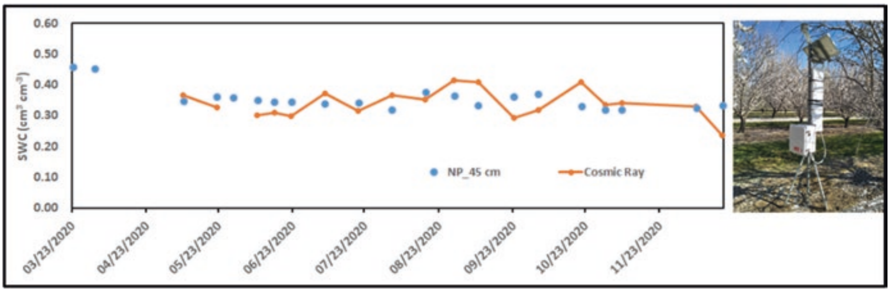

Fig. 3.4 Time series of aerial averaged soil water content measured using cosmic-ray neutron probe compared to in situ neutron probe at 45 cm. NP refers to neutron probe and SWC refers to soil water content

agreement between the CRNP and the in situ soil water sensors at 45 cm depth (Fig. 3.4). However, CRNP sensors are currently expensive and are mostly used in research.

3.4.2 Tree Water Status Monitoring

In orchard water management, measuring the tree water status is the best water stress indicator. For example, in almonds, midday stem water potential (SWP) has been proven the best indicator of tree water status because it integrates soil factors for the entire root zone and environmental conditions (Fulton et al., 2014). SWP is dynamic and is not only affected by soil water content but also environmental conditions. SWP changes diurnally and seasonally, and it is more difficult to develop absolute general thresholds for triggering irrigation than when monitoring soil water content. For this reason, SWP measurements have to be benchmarked against a reference or baseline SWP for non-water-stressed trees in the same environment. Measurements of midday SWP are usually taken around solar noon or between 1:00 and 3:00 p.m. when SWP is minimum (i.e., most negative). The procedure for measuring SWP involves placing a mature lower canopy shaded leaf into an aluminum foil bag for about 15 min, followed by removing the leaf and immediately placing it in a pressure chamber, pressuring the chamber until water begins to come out of the cut end; the pressure reading represents the SWP. In orchard irrigation scheduling, SWP is preferred to leaf water potential (the leaf is not placed in an aluminum bag before placing it in the pressure chamber) because it is less sensitive to atmospheric demand and is more representative of the water status of the entire tree. Measurement of midday SWP is labor-intensive, contributing to its lack of widespread adoption outside of research, as shown in Table 3.1.

Recently, new sensors have been developed that continuously measure SWP. These sensors can be broadly categorized into two types: osmometers and micro-tensiometers. The osmometer sensors measure pressure changes caused due

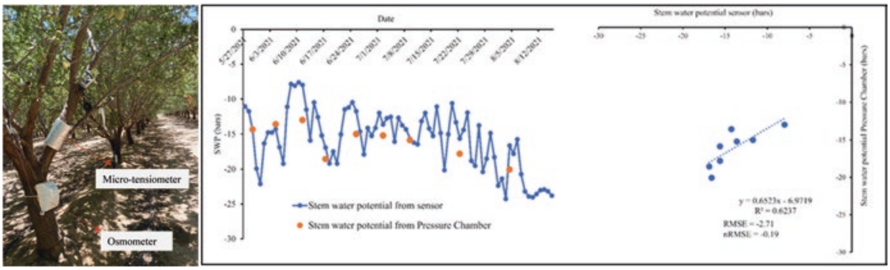

Fig. 3.5 Comparing stem water potential from a FloraPulse micro-tensiometer to a pressure chamber in nonpareil almond trees near Corning, California. nRMSE refers to the normalized root mean square error

to changes in osmosis of the chamber fluid. The sensor has a semipermeable membrane that allows water movement between the tree xylem and the sensor fluid chamber (Meron et al., 2015). The change in pressure measured by the sensor can be interpreted in terms of stem water potential. Other types of SWP sensors act as micro-tensiometers. Micro-tensiometers are based on tensiometry, a technique for measuring the chemical potential of stretched liquid water based on a thermodynamic equilibrium between the stretched water and its vapor (Pagay, 2014; Pagay et al., 2014). Figure 3.5 compares FloraPulse stem water potential to pressure chamber measurements in nonpareil almond trees near Arbuckle, California. Overall, there is a good agreement between SWP sensors and the pressure chamber.

Besides SWP sensors, another type of sensor used to measure tree water stress is the dendrometer. Dendrometers measure the mean daily shrinkage (MDS). MDS refers to the difference between daily maximum and minimum trunk diameter. Soil water depletion or more demand from weather causes the trunk to shrink more each day. Preliminary research has shown a good correlation between MDS and SWP; commercially available dendrometer services include Phytech (https://www.phytech.com/). Other proximal sensors, such as the leaf monitor that monitors the leaf temperature of a single leaf in combination with crop water stress index (CWSI), have been developed and evaluated in almond orchards but still need more development and testing to be ready for adoption by growers (Dhillon et al., 2014; Meyers et al., 2019; Drechsler et al., 2019).

3.4.3 *Remote Sensing of Evapotranspiration*

Compared to the traditional approaches of using reference evapotranspiration and a single crop coefficient, remote sensing of evapotranspiration based on aerial or satellite platforms allows for estimation of ETa at a high spatiotemporal resolution, making it suitable for smart irrigation management. Various models are used for estimating ETa using remote sensing, and they vary widely in complexity. They can be broadly categorized into two groups: (1) semi-empirical models or those that use vegetation indices from surface reflectance data to estimate crop coefficients (Kc) and then calculate ETa as the product of the remotely estimated Kc and ETo and (2) those based on biophysical processes such as the surface energy balance. Based on these two approaches, examples of commercially available products are IrriSat (https://irrisat-cloud.appspot.com/) and IrriWatch (https://www.irriwatch.com/en/), respectively.

A major limitation of the semi-empirical remote sensing-based ETa models is the requirement to know the relationship between Kc and vegetative indices for a given crop, limiting its wide-scale adoption because these relationships have not been locally developed for most crops. Remote sensing-based ETa models based on the surface energy balance can be subdivided into one-source and two-source models (Xue et al., 2020).

One-source remote sensing-based ETa models consider soil and vegetation as a single source with regard to land surface temperature and land surface energy exchange (Bastiaanssen et al., 1998). On the other hand, two-source remote sensing-based models consider land surface temperature from soil and plant canopy as two separate sources, and the corresponding energy fluxes for evaporation and transpiration are estimated separately (Norman et al., 1995). A major limitation of two source-based models is that they require high-resolution images of land surface temperature that can be obtained using thermal cameras mounted on UAVs or airplanes; nevertheless, such images are not readily available, especially at a large scale.

Single-source models based on satellite imagery are the most common in commercial almond production. The most common remote sensing-based single-source ETa models include the Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al., 1998), the Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) (Allen et al., 2007), the Simplified Surface Energy Balance (SSEB) (Se-nay et al., 2007), and the Surface Energy Balance System (SEBS) (Su, 2002). Validation of some of these models in commercial almond orchards is an ongoing activity as algorithms get refined, and the resolution of remote sensing imagery improves. While these models have been around for more than a decade, they have been limited to research. However, recent advances in cloud computing and improvements in algorithms have allowed private service providers to develop pipelines that allow them to serve remotely based ETa data on an orchard-by-orchard basis through the web or mobile apps (e.g., IrriWatch, and Agralogics/Jain). For example, Fig. 3.6 compares remotely estimated ET using the SEBAL model embedded in IrriWatch to ETa from an eddy covariance station in an almond orchard. The results show that remotely sensed ETa is acceptable for irrigation management with an RMSE of less than 1.0 mm/day. Open-source efforts by various patterners, e.g., NASA and Google Earth Engine, are ongoing to deliver satellite-based remotely sensed ETa to growers, e.g., OpenET (https://openet-data.org/).

UAVs and airplane platforms provide opportunities to obtain high-resolution thermal and multispectral imagery that can be used to estimate ETa at an individual tree scale. However, the high spatial resolution imagery is used with energy balance algorithms developed for satellite platforms. Therefore, there is a need to validate

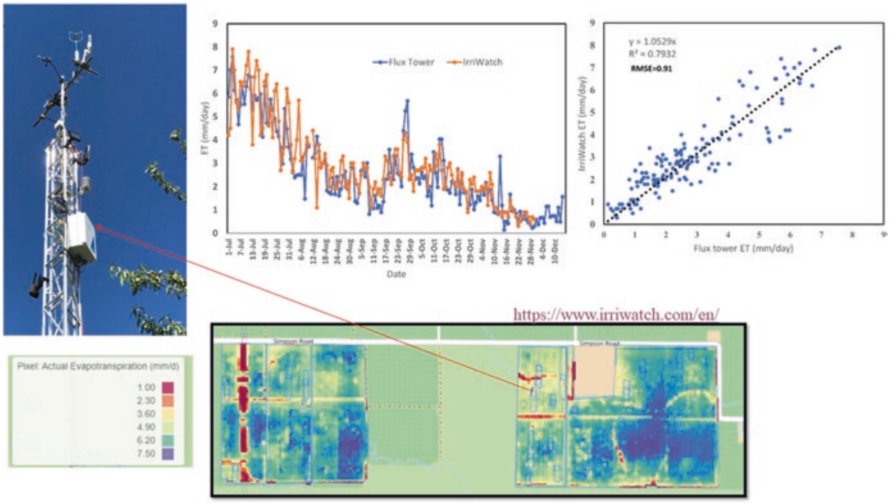

Fig. 3.6 Validation of a commercially available remotely sensed actual evapotranspiration (ETa) service to observed ETa from an eddy covariance flux tower in an almond orchard at the Esteve Ranch located near Corning, California

how well the surface balance models developed for satellite platforms work with high spatial resolution imagery (e.g., Niu et al., 2020; Peddinti & Kisekka, 2021).

The ETa estimated from remote sensing is typically used to evaluate the water balance. In orchard water management, where micro-irrigation is the dominant irrigation method, the ETa is summed since the last irrigation to determine the amount of water to apply for the next irrigation. Under micro-irrigation, the goal should be to irrigate as frequently as practical, subject to soil infiltration characteristics, water, labor availability, and growth stage. In almond orchards, our observations have indicated that the effective root zone is approximately 1.2 m.

The ideal orchard water management strategy should combine ETa-based monitoring with SWP and soil water monitoring. However, if cost is a limitation, a combination of these irrigation scheduling methods should be used.

3.5 Strategies for Reducing Water Use in Orchards

In many regions of the world with Mediterranean climates where nuts and certain fruits are produced, water supplies are constrained by climate change and increased demand from other beneficial uses. In such situations, available water is insufficient to meet full crop evapotranspiration. Examples of strategies that can be employed to cope with drought or reduce consumptive water use in crops such as almonds are discussed below.

3.5.1 Irrigation Systems Related Strategies

Improving distribution uniformity (DU) and irrigation application efficiency (AE) is critical to reducing water use in almonds without negative impacts on the grower's economic returns. Low DU can result in parts of the orchard being overwatered while other parts receive very low irrigation water, and severe stress is triggered. With micro-irrigation, almond growers typically aim to achieve a DU of 90% or higher to ensure that all trees have equal opportunity to the applied irrigation water. High AE aims to reduce nonproductive water loss, e.g., runoff and deep percolation. High AE ensures that most of the applied water is used for evapotranspiration. High DU and AE start with a good irrigation system design, smart irrigation scheduling, and an optimal plan for operation and maintenance. Monitoring flow and pressure at critical points within the irrigation network is recommended to ensure the system is operating as designed. New remote sensing technologies, e.g., transpiration uniformity discussed earlier, provide feedback that can complement periodic measurements of DU in the orchard. New irrigation design paradigms such as ZIM or VRI can help growers achieve high DU and AE in orchards underlined by varying soils. Fereres et al. (2012) recommend that under situations of limited water, growers should mine the stored soil water in the root zone as much as possible such that the season ends with a dry profile that can be refilled by winter rainfall. However, this strategy will only work in situations where the drought is temporary.

3.5.1.1 Deficit Irrigation as a Strategy to Reduce Orchard Water Use

Deficit irrigation (DI) refers to irrigation management in which the applied water is less than the orchard ETa requirements (Fereres et al., 2012). Deficit irrigation can be broadly categorized into sustained deficit irrigation (SDI) and regulated deficit irrigation (RDI). Under SDI, a constant percentage of ETa or full irrigation is applied throughout the season. In contrast, in RDI, deficits are implemented based on the growth stage to reduce water use or improve nut quality. Any DI strategy aims to have minimum impact on economic returns while reducing water use. Several studies have been conducted in California to study almond response to deficit irrigation (Shackel, 2004; Goldhamer et al., 2006; McCullough-Sanden et al., 2020; Drechsler & Kisekka, 2021).

Successful implementation of deficit irrigation under moderate water deficits in almonds requires understanding the sensitivity of different growth stages to water stress. Water stress affects trees earlier in the season, from leaf out through shoot growth and development of terminal and lateral buds (Fulton et al., 2001). During this period, rapid vegetative growth is necessary for canopy development, and fruit positioning and stress should be avoided or minimized to avoid yield reductions in current and future years. Goldhamer et al. (2006) reported achieving reductions in 15–30% water use with SDI without significant reductions in kernel yield. Almond trees can tolerate water stress during the fruit growth and development stage. The

2 months before harvest provides the time to achieve water reductions via deficit irrigation (Shackel, 2004). Reductions in kernel weight and poor hull split caused by water stress have been reported, and to mitigate this effect, at least 25 mm of irrigation should be applied 2 weeks before hull split. Using various levels of RDI, McCullough-Sanden et al. (2020), in a 5-year study in Kern County, California, reported a 15.4% reduction in yield from a 30% reduction of full irrigation. In a 3-year RDI by variety study near Arbuckle, California, Drechsler and Kisekka (2022) reported no significant differences in kernel yield between 100% ET and 50% and 75% ET treatments in mature nonpareil, butte, and Aldrich varieties with reduction implemented after 1% hull split. During the post-harvest growth stage, bud differentiation continues through September, and moderate water deficits do not affect subsequent year's nut numbers (Goldhamer et al., 2006). However, severe stress during the post-harvest period has been reported to reduce fruit set for the following year. Severe water stress during this period should be avoided, but the potential for water-saving will depend on the atmospheric evaporative demand and the length of the post-harvest period.

Under extreme drought, deficit irrigation can be used to cope with a reduced water supply, enhancing tree survival. Irrigation should be withheld during the early growth stage until stem water potential reaches −12 to −14 bars. Irrigation should be withheld during the fruiting and development growth stages until stem water potential reaches −20 to −22 bars (Fulton et al., 2001). Field observations during the 2021 drought noted that stem water potential reached −27 to −30 bars without significant leaf drop. It is worth noting that this severe DI strategy will reduce fruit weight in the year it is implemented and will reduce the fruit number in subsequent years. However, this might be the only option under multi-year droughts and regulated groundwater pumping.

3.5.1.2 Reducing Soil Evaporation

Light irrigations should be avoided because they are associated with a high proportion of nonproductive soil evaporation losses. Soil amendments such as nut hulls and shells can be applied as residue cover to reduce soil evaporation and improve soil health. The success of this management strategy is tied to ongoing developments in off-ground harvesting in the case of almonds. This research is still new, and no generalized recommendations have been developed.

3.6 Conclusions

Orchard water management under changing climate and increased demand from other beneficial uses requires the adoption of smart irrigation. We reviewed the latest advances in irrigation systems, including zone irrigation management and variable rate irrigation. For the benefits of ZIM and VRI to be fully realized, growers need to couple these advanced systems with smart irrigation scheduling that applies the right amount of water at the right time and in the right place. Based on literature and field experience, irrigation scheduling strategies should involve the monitoring of soil water status using a wide range of sensors to manage the soil water reservoir in the root zone; monitoring of stem water potential using micro-tensiometers, osmometers, or pressure chambers to determine when irrigation should be triggered; and monitoring of ETa using remote sensing techniques to determine how much water to apply in different parts of the orchard. For example, in California, the Almond Board of California has pledged to reduce the amount of water required to grow a pound of almonds by 20% by 2025. To achieve this sustainability goal and cope with droughts, almond growers need to reduce the amount of water applied.

To reduce orchard water use without negatively impacting economic returns, growers need well-designed, well-operated, and well-maintained irrigation systems that achieve high distribution uniformity and application efficiencies. Finally, optimum reduction of orchard water use requires implementing deficit irrigation strategies informed by knowledge of the sensitivity of different almond growth stages to water stress. Reductions by 15 to 30% of full irrigation have been reported without significant reductions in kernel yield. Although the concepts covered in this book chapter focus on almonds, some may apply to other crop orchards, e.g., pistachios, walnuts, and fruit orchards.

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Chapter 4
Vineyard Water Management

María Paz Diago

Abstract Although grapevine is a drought-tolerant species, it has elevated water requirements to complete its growth cycle, which, in the end, coincides with the driest months of the year. As a result, irrigation is increasingly being applied to vineyards worldwide. Moreover, a period of strong variability and uncertainty in water availability is forecast due to climate change; therefore, improving viticulture's irrigation scheduling is critical for achieving a sustainable and productive grape and wine industry. Effective implementation of sustainable water management can only be based on objective and representative monitoring of the crop water status. Since many of these classical procedures are either destructive, tedious, or difficult to automate, noninvasive technologies have been developed in the last decade to assess vineyard water status spatial variability. Likewise, novel approaches based on soil electrical conductivity, thermography, NIR spectroscopy, and multispectral and hyperspectral imagery—remote (from aircraft or drones) or proximal (from handheld devices or ground-moving vehicles)—are discussed. Also, use cases that utilize these techniques to implement more precise, smart irrigation management are described. Finally, alternative practices to reduce water consumption in viticulture are also provided.

4.1 Introduction

Even though the grapevine is a drought-tolerant species, it has elevated water requirements to successfully complete its growth cycle (Costa et al., 2016), which, in the end, coincides with the driest months of the year. The adoption of vineyard irrigation, which was banned or subjected to very strict regulations until not so long ago in many wine regions across Europe, is rising steadily worldwide.

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Improving viticulture's water management is therefore critical to achieving a sustainable and productive grape and wine industry. Nowadays, the effective implementation of sustainable water management and irrigation in viticulture calls for objective and representative monitoring of the crop water status. Hence, there is a need to provide support and applicable tools to grape growers to move from their traditional water status monitoring (if any) and irrigation practices to modern, more precise, reduced demand systems and technologies (Chartzoulakis & Bertaki, 2015).

4.2 Current Methods for Vineyard Water Status Monitoring

As in fruit orchards, the timing and extent of irrigation can be defined using several indirect methods, including soil measurements, water budget estimates, and environmental modeling, or direct, plant-based approaches (Rienth & Scholasch, 2019).

Soil-based methods focus on measuring soil moisture. Although they enable continuous, remotely accessed data (also during wintertime, to assess the soil refilling capacity), they have to be placed in representative locations within the vineyard to account for the inherent spatial variability of soil, which may require a high number of units. Machinery intervention and tillage may also pose a risk of sensor damage, and in some vineyards of gravelly and stony soils, installing these sensors is not feasible. Moreover, once the soil sensor is buried and placed, its measurement spans along a limited horizontal and vertical soil volume, which is a shortcoming, as grapevine roots may explore beyond the targeted soil volume, and the reading will not bring accurate water availability to the plant (Rienth & Scholasch, 2019). Some commercial portable probes are available to get information about vertical soil moisture distribution. These can be inserted in previously installed access tubes (of different depths between 0.7 and 1.6 m) across different representative locations within the vineyard to assess the water soil profile at given intervals of 10 cm. While these probes provide useful information about the differential soil moisture at different depths and, in some cases, information about the soil's salinity, their costs may limit their deployment and are difficult to be automated.

Vineyard water usage can also be appraised by determining the total evapotranspiration (ETa) using atmospheric measurements, soil water balance, and remote imagery (Xia et al., 2016). However, plant-based methods have been described as the most adequate for assessing grapevine water status, as the plant integrates both soil and atmospheric demand conditions (Jones, 2004). Since its first introduction in the mid-1960s (Schölander et al., 1965), pressure chamber remains an important irrigation management tool in commercial vineyards today (Williams, 2017). It is used to assess the vine water potential (Ψ), either pre-dawn (Ψ_{PD}), leaf (Ψ_l), or stem water potential (Ψ_s), whose advantages and disadvantages have been recently reviewed (Santesteban et al., 2019). Thresholds of water potential values for

Table 4.1 Threshold values of pre-dawn water potential (Ψ_{PD}), leaf water potential (Ψ_l), and stem water potential (Ψ_s), expressed in MPa for different levels of grapevine water stress

Water stress level	Ψ_{PD}	Ψ_l	Ψ_s
No stress	> −0.2	> −0.9	> −0.8
Low	−0.2 to −0.3	−0.9 to −1.1	−0.8 to −1.0
Medium	−0.3 to −0.8	−1.1 to −1.6	−1.0 to −1.4
High	< −0.8	< −1.6	< −1.4

Adapted from van Leeuwen et al. (2009) and Mirás-Avalos and Araujo (2021)

different plant water status situations are reported in Table 4.1. Both Ψ_{PD} and Ψ_s are probably the most used vine water potential indicators to drive irrigation scheduling in commercial vineyards.

Another relevant plant-based method builds on the preference of the enzymes responsible for plant photosynthesis for the ^{12}C isotope (which is predominant in the atmosphere (Craig, 1953)) versus the ^{13}C isotope (Farquhar et al., 1980). This phenomenon is called carbon isotope discrimination. This prevalence is less marked under water stress conditions, and sugars produced by the plants contain more ^{13}C than those produced when no water limitation exists. The ratio between the quantities of the two isotopes ($^{13}C/^{12}C$) in the sugars of the berries is denoted as $\delta^{13}C$ and is considered an integrative indicator of the water deficit suffered by the grapevine during the ripening process. $\delta^{13}C$ ranges from −27/1000 (absence of water stress) to −20/1000 (severe water stress) and has proved to be well correlated with plant water potential (Gaudillère et al., 2002). Since this method can only be applied at the end of the growing season, its utility in driving day-to-day irrigation decisions is limited. Nevertheless, it may provide valuable information to evaluate past agronomic and water management practices and define future irrigation approaches based on lessons learned (van Leeuwen et al., 2009).

Among other plant-based methods, gas exchange sensors, sap flow meters, and dendrometers can be listed. Their physiological fundamentals are sound; however, either the cost and complexity of the instrumentation required or the interpretation of the results they generate renders them of limited utility for commercial vineyard management and sets them aside mostly for research purposes.

Although very reliable and informative, these conventional plant-based methods are either destructive, complex, or time- and labor-demanding (Fernández, 2014), hindering their utilization in commercial vineyards. Furthermore, many of these tools measure only a limited (usually small) number of vines, making them unsuitable for detecting spatial variation in water status within a vineyard plot (Acevedo-Opazo et al., 2008). Therefore, the paragon method to assess plant water status should be reliable, non-destructive, sensitive to water fluctuations, capable of responding fast, inexpensive, and easy to operate and interpret (Fernández, 2014). Besides, should the spatial variability of the vine water status within a vineyard need to be assessed, this ideal method must be automated.

4.3 Vineyard Spatial Variability

The spatial variability of grapevine water status within a vineyard is mostly explained because land and soil are variable. This involves that water and nutrient availability inter- and intra-plots may be changing, which has a strong influence on both plant development and physiology and crop production and composition (Bramley & Hamilton, 2004; Bramley, 2005). In this context, the usefulness of high spatial resolution information regarding plant water status zones within plots has been advised (Acevedo-Opazo et al., 2010; Cohen et al., 2017) to provide grapevines under different water requirements with different irrigation doses, that is, smart irrigation.

4.4 Noninvasive Technologies for Vineyard Water Status Monitoring

To overcome most of the pitfalls of classical plant-based methods, alternative automated solutions based on non-destructive technologies are being developed to assist in assessing vineyard water status spatial variability (Tardaguila et al., 2021). While some are already commercially available to some extent, others are still under development and constitute the state-of-the-art methods to determine the necessary water input for smart irrigation strategies.

An important group of technologies is those linked to remote (far from the ground) and proximal (close to the ground) sensing, which gather information about plants and soil. Most of these are based on the interaction between electromagnetic radiation (at different wavelength ranges) and a given organ or plant tissue. Radiation emitted by the sun or any internal light source reaches the target of interest and then travels back to a receiving or recording device detected by passive or active sensors, respectively. While active sensors provide their energy source or illumination, passive sensors can only be used when external, natural energy (e.g., sun radiation) is available.

To assess grapevine water status and corresponding vineyard spatial variability of this variable, methodologies based on two main non-destructive technologies, thermography and VIS-NIR spectroscopy-related methods, are under development. In both cases, information and data gathered with the sensors are then validated against a plant-based water status reference method, typically Ψ whose threshold values (Table 4.1) are more comprehensive to drive irrigation scheduling.

4.4.1 Thermography and Infrared Radiometry

Infrared thermography is the science of detecting infrared energy emitted from an object, transforming it into apparent temperature, and then representing the result as an infrared image. Therefore, thermography allows the visualization of differences in surface temperature from emitted infrared radiation within the wavelength range 1.3–15 μm.

4.4.1.1 Thermal Stress Indices

In agriculture, thermography has been mainly used to assess plant water status based on the relationship between the leaf stomatal aperture and surface temperature (Jones et al., 2002). Water loss through the stomata occurs when leaves transpire and leaf temperature decreases. However, isohydric plants respond to water deficit conditions by closing their stomata. As a result, transpiration stops, stomatal conductance is limited, and leaf temperature increases. Leaf temperature is then related to stomatal conductance when environmental conditions are constant (Jones, 1999), but leaf temperature can be affected by fluctuations in the environmental conditions (e.g., cloudiness, wind). Thermal stress indices such as the Crop Water Stress Index (CWSI) (Eq. 4.1) (Idso et al., 1981) and the Stomatal Conductance Index (Ig) (Eq. 4.2) (Jones et al., 2002) have been developed to mitigate such fluctuations.

$$\mathrm{CWSI} = \frac{T_l - T_{\mathrm{wet}}}{T_{\mathrm{dry}} - T_{\mathrm{wet}}} \tag{4.1}$$

$$I_g = \frac{T_{\mathrm{dry}} - T_l}{T_l - T_{\mathrm{wet}}} \tag{4.2}$$

Compounding these indices requires the definition of two reference temperature values, denoted as T_{dry} and T_{wet}, which are used to normalize the leaf temperature (T_l). While T_{dry} represents the highest possible leaf temperature under those specific environmental conditions (i.e., a non-transpiring leaf in which all stomata are closed), T_{wet} is a proxy of the lowest potential leaf temperature in that same environment (i.e., a fully transpiring leaf with all stomata open). Leaf temperature should lie within the temperature range anchored by T_{dry} and T_{wet}. Different approaches have been used to compute these two reference values (Zhou et al., 2021). Although recent studies have avoided the use of reference temperatures in the assessment of grapevine Ψ_s with satisfactory results (Gutiérrez et al., 2018), proper comparison of plant water status as assessed by thermography among plots or several dates and seasons for a given vineyard can only be conducted using thermal indices, which require the use of T_{dry} and T_{wet} values. So far, this is certainly one of the main obstacles that have hindered the automation and further implementation of this technology in productive vineyards.

4.4.1.2 Remote and Proximal Thermal Imaging

Over the last decades, technological advances in thermal imaging have enabled new opportunities to acquire plant thermal responses to water status changes (Baluja et al., 2012). Likewise, thermal cameras can be used as portable devices (Pou et al., 2014) or even in combination with smartphones (Petrie et al., 2019) to estimate plant water status and assist in the setup of irrigation schedules. However, time and labor demand, together with the limited number of manual measurements, remain pitfalls. Aerial thermography has partially solved the latter, which can cover large field extensions (Zhou et al., 2021).

At the regional level, Pagay and Kidman (2019) surveyed 11 experimental sites (100 ha of vineyards of Shiraz and Cabernet Sauvignon cultivars) across the Coonawarra wine region (South Australia), using airborne (a manned fixed-wing aircraft was used) thermal imagery over two consecutive seasons. High-resolution airborne thermal imagery enabled the assessment of vine water status across a whole viticultural region. Remotely sensed thermal indices were mostly in agreement with ground-based measurements of vine water status, particularly under environmental conditions favoring maximum leaf transpiration. From a technological standpoint, the high spatial resolution of the thermal camera (640 × 512 pixels, yielding an angular field of view of 25°) enabled the precise separation of inter-row and vine signals. Similar findings were reported by Bellvert et al., (2016). They demonstrated that thermal imagery from piloted aircraft enabled the development of regulated deficit irrigation (RDI) strategies in Chardonnay vines without any negative effect on yield and wine composition. Additionally, aerial thermal imagery can successfully identify irrigation inefficiencies that may not be evident at ground level (Pagay & Kidman, 2019).

In case a limited number of vineyard plots have to be monitored, or even a single vineyard has to be surveyed using aerial thermal imagery, UAVs are recommended (Baluja et al., 2012; Sepúlveda-Reyes et al., 2016). In some crops, such as grapevines, the spatial resolution associated with data from aerial surveys may be insufficient, and several meters of canopy may be shrunk into a reduced number of pixels, therefore losing information. That is the case in many vertical shoot positioning (VSP) vineyards, where vegetation is well placed between catch wires. For these, canopies will only have 30–50 cm width of vegetation from a zenithal point of view, compared to orchard trees (González-Dugo et al., 2013), where higher canopy projected areas can be observed (Fig. 4.1c, d). Besides, remote (either from manned or unmanned aerial vehicles) thermal imagery-derived pixels often mix canopy and soil information (if the camera resolution is not high), which complicates further analyses as they need to be effectively separated.

This opens up possibilities for the development of proximal, on-the-go thermographic solutions capable of gathering detailed canopy information from a close lateral (Fig. 4.1a, b) point of view (Costa et al., 2019) and of covering large areas to enable the monitoring of the vineyard water status variability (Gutiérrez et al., 2018).

Likewise, ground lateral thermography of tempranillo (*Vitis vinifera* L.) grapevines has been successfully tested using thermal cameras on the go from a moving

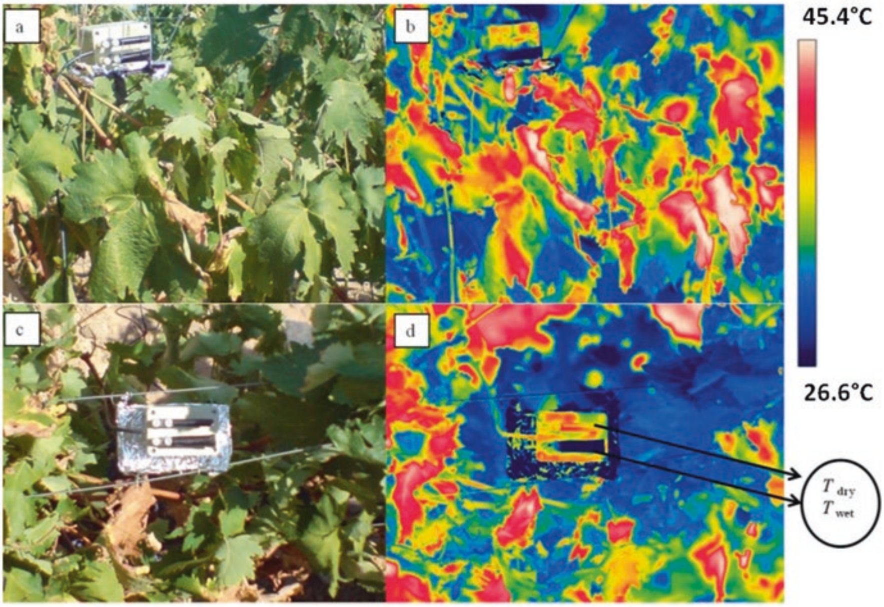

Fig. 4.1 Lateral (**a**, **b**) and zenithal (**c**, **d**) visualization of the canopy using aerial and proximal thermography, respectively. Two artificial leaves (Evaposensor, Skye Instruments Ltd., UK) used to compute reference T_{dry} and T_{wet} are shown in all subplots

vehicle (5 km/h), operating at 1.20 m from the canopy (Gutiérrez et al., 2018; Gutiérrez et al., 2021). Good relationships (R^2 ~ 0.60–0.80; root mean square error of prediction (RMSEP) ~0.123–0.190 MPa) between the predicted and observed Ψ_s were obtained. Two artificial leaves (Evaposensor, Skye Instruments Ltd., UK) were used to estimate T_{wet} and T_{dry} reference values (Fig. 4.1).

4.4.1.3 Infrared Radiometers

Regardless of whether thermal imagery is acquired remotely or proximally, its processing to extract the relevant canopy information is not simple and requires time and specific knowledge. Infrared radiometers can be considered a simpler version of thermal cameras. While thermal cameras acquire 2D images in which a temperature value is associated with each pixel, an infrared radiometer provides an averaged value of the target's surface temperature of the measuring spot. In a comprehensive review on the use of ground-based thermography to assess plant water status in agriculture, the advantages of infrared radiometers vs. thermal cameras were summarized (Maes & Steppe, 2012). Though these types of sensors (e.g., IR SI-421, Apogee Instruments, Inc., Utah, USA) are often designed to be installed on static poles (they are ruggedized to properly function outdoors for a long time), attempts to install and operate them from ground-moving vehicles have been recently reported (Fernández-Novales et al., 2021) (Fig. 4.2).

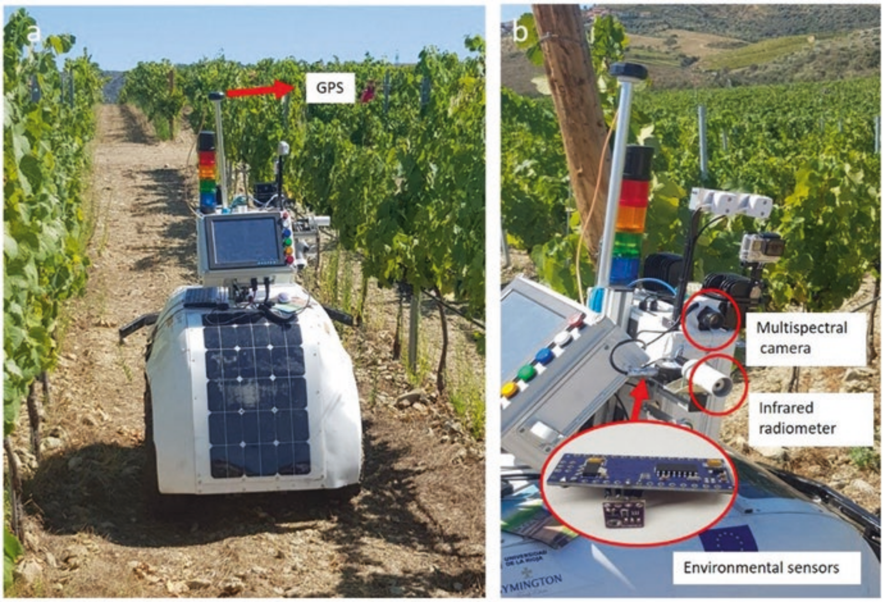

Fig. 4.2 (**a**) Prototype of the unmanned ground vehicle developed under the VineScout (www.vinescout.eu) project to automatically assess vineyard water status. (**b**) Close-up of the infrared radiometer, multispectral camera, and suite of environmental sensors used to model leaf water potential (Ψ_l)

In this work, a novel approach was tested that combined infrared radiometry, multispectral imaging (NDVI), and a set of environmental sensors (T_{air}, HR%, P_{atm}) to avoid the use of reference temperatures. The sensors were mounted on an autonomous ground vehicle (Fig. 4.2) to assess the plant water status variability within a commercial vineyard (*Vitis vinifera* L. cultivar Touriga Nacional).

One important thing to consider when using an infrared radiometer is the size of its measuring window. Depending on the design of the radiometer, its field of view, and the distance to the target, its measuring spot size may change. This is relevant because a large measuring spot size may include a substantial quantity of pixels corresponding to canopy elements (e.g., berry, wood, gap, wire) other than leaf, which may add noise to the average temperature record.

4.4.1.4 Additional Physiological and Practical Considerations Regarding Thermography

The interpretation of canopy thermal data may not be simple, as leaves in the canopy may undergo distinct environmental conditions and leaf orientations, both factors potentially affecting the recorded temperature (Poirier-Pocovi & Bailey, 2020). Substantial variation in computed CWSI can be found in different canopy parts, although the diurnal trends are similar (Prueger et al., 2019). Furthermore, the highest CWSI values are usually measured in the morning, while the lowest are computed in the late afternoon (Prueger et al., 2019).

When validating leaf thermal data (which is closely related to gs and stomata regulation) with water potential, it has to be understood that different responses to water deficit between stomata regulation and plant hydraulics (isohidricity level) would potentially cause divergences in the behavior of plant temperature versus plant water potential.

The use of CWSI for assessing vineyard water status requires calibration to account for the effects, primarily of the phenological stage and of variety. Once calibrated, this can be successfully applied to other vineyards and seasons (Bellvert et al., 2015).

4.4.2 NIR Spectroscopy, Multispectral Imagery (MSI), and Hyperspectral Imaging (HSI)

The NIR region is the part of the electromagnetic spectrum between 750 and 2500 nm. It is related to the absorption of energy from molecules or chemical constituents related to the overtones and combinations of fundamental vibrations caused by the stretching and bending of N–H, O–H, and C–H bonds. The water molecule, a predominant component of leaves, can partially or fully absorb the light at given wavelengths of 760, 971, or 1450 nm (O–H overtones) and a combination band of 1940 nm (Nicolai et al., 2007).

4.4.2.1 Working with the Whole Spectrum

In the last decade, a few studies have investigated the potential of near-infrared (NIR) spectroscopy to enable rapid monitoring of plant water status at the leaf level in grapevines (De Bei et al., 2011; Tardaguila et al., 2017) using portable devices (Fig. 4.3).

The simplicity of portable devices (in which calibration curves against the variables of interest can be built, therefore enabling an instantaneous reading) is counterbalanced by the impossibility of automation, hence providing many measurements required to assess vineyard spatial variability. To overcome this lack of automation, the capability of contactless NIR spectroscopy (1200–2100 nm) mounted on an all-terrain vehicle (Fig. 4.4) for the on-the-go estimation of grapevine Ψ_s has been tested (Diago et al., 2018). Similarly, Fernández-Novales et al. (2018) successfully discriminated the vines within a vineyard among three different water statuses (low, medium, and high), with a percentage of correct classification superior to 72%.

Although successful, several issues prevent this NIR spectral methodology from being easily transferred and commercially available to the wine industry. In first place, the high cost and dimensions of the current spectrometers used for on-the-go

Fig. 4.3 Spectral measurement on the adaxial side of leaves using a handheld NIR (1600–2500 nm) spectrophotometer. (microPHAZIR, Thermo Fisher Scientific)

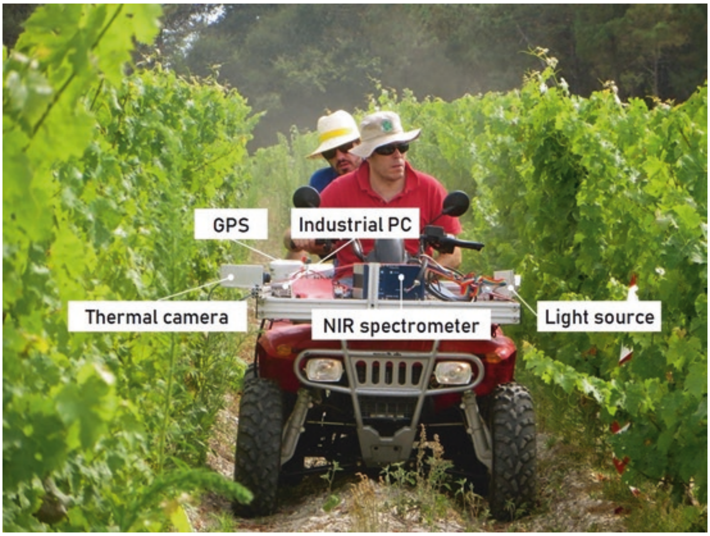

Fig. 4.4 Setup to assess grapevine water status using proximal, on-the-go thermography and NIR spectroscopy

contactless monitoring, although some trials involving miniaturized, lower-cost spectrophotometers (e.g., NIR 1.7, INSION GmbH, Obersulm, Germany) are providing satisfactory results (Fig. 4.5). Secondly, the requirement of processing the whole spectrum, potentially containing redundant information, which accounts for large computational time and capacity, which may hamper the real-time estimation of plant water status.

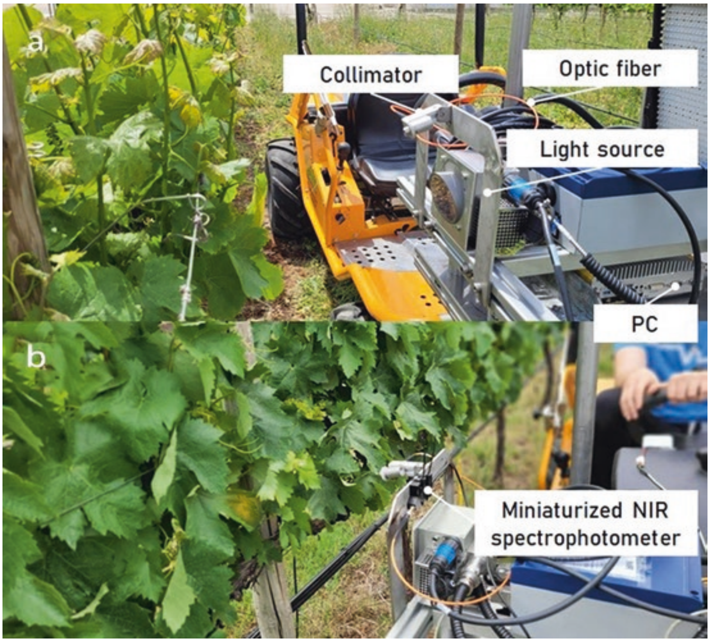

Fig. 4.5 Experimental setup (**a**) to assess grapevine water status using a (**b**) miniaturized NIR spectrophotometer from a ground-moving vehicle

4.4.2.2 Spectral Indices

Simplified spectral information can be gathered from spectral indices, defined as a spectral transformation (e.g., ratio, normalization) of two or more bands designed to enhance the contribution of vegetation properties. In agriculture, spectral indices computed either from spectroscopy data or from multispectral (MSI) or hyperspectral imagery (HSI) typically relate to a plant's vigor and photosynthetically active biomass (e.g., NDVI, PCD). However, some have correlated well with plant water status indicators, like the Photochemical Reflectance Index (PRI), which measures the light-use efficiency of foliage and is primarily used as an indicator of water stress (Peñuelas et al., 1995).

Toward assessing grapevine water status, Poças et al. (2020) and Romero et al. (2018) combined spectral data with several machine learning algorithms to develop predictive models of Ψ_{PD} and Ψ_s, respectively. Spectral indices such as the NRI554,561 (Poças et al., 2017), the WI900,970 (Peñuelas et al., 1997), and the Optimized Soil Adjusted Vegetation Index (OSAVI) were included in the models. These showed good performance in predicting plant water status and became the basis for potential applications of improved irrigation scheduling based on MSI or HSI gathered from aerial or satellite platforms.

4.5 Strategies for Reducing Water Use in Vineyards

In many wine-growing regions, particularly in Europe, vines are still rainfed without any additional watering apart from rainfall. While this strategy can be considered as the one producing the lowest possible blue water footprint (Rienth & Scholasch, 2019), additional agronomical approaches can be put in place to maximize water use efficiency in the vineyards. Most of these strategies have been recently reviewed by Romero et al. (2022). They include: (i) an adequate choice of genetic material, both rootstocks and cultivars, better adapted to water scarcity; (ii) improvement of soil health, including the use of mulching and cover crops among other practices; and (iii) canopy management practices and choice of trellis, row orientation, and planting density.

Recently, the use of particle film technology (engineered kaolin) led to improved WUEi by 18% compared to untreated vines at the same time that anthocyanins increased a 35% and wine quality perception (Brillante et al., 2016). Of all potential solutions to maximize water use efficiency in grapevines, optimized irrigation emerges as the most efficient tool for vineyard sustainability in relation to water consumption.

The three most-studied irrigation approaches in terms of sustainability are sustained deficit irrigation (SDI), regulated deficit irrigation (RDI), and partial root-zone drying (PRD). In viticulture, DI is a common and advisable cultural practice that induces some water stress in the vines, beneficial for yield regulation and grape and wine quality (Roby et al., 2004; Edwards & Clingeleffer, 2013). An equal proportion of ETc is applied in SDI during the whole phenological cycle. This results in a constant enhancement of water stress during the growing season. In contrast, in RDI, the proportion of ETc returned to vines during the growing season is variable, leading to more severe drought stress at a specific phenological stage (Romero et al., 2022). PRD involves drying part of the root system while simultaneously maintaining the remaining roots in a well-watered condition. Since the effect is temporary, it is, in fact, necessary to maintain part of the root system dry and to apply water to the other side of the vine for a particular duration and then interchange the other side for periods of 7–14 days (Romero et al., 2016). A comprehensive review of the application of SDI, RDI, and PRD in vineyards can be found in Romero et al. (2022).

4.6 Smart Irrigation Scheduling

Smart irrigation scheduling in vineyards typically requires delineating homogeneous zones within the plots. In addition to the noninvasive technologies already discussed for vineyard monitoring, multispectral imagery for vine vigor assessment (e.g., based on NDVI or other vegetation spectral indices) or soil electrical resistivity is often used to define homogeneous zones.

During the last two decades, spectral vegetation indices such as Plant Cell Density (PCD) and Normalized Difference Vegetation Index (NDVI), computed from multispectral imagery acquired either from aerial platforms like satellites (Landsat-8, Sentinel-2), manned and unmanned aerial vehicles (Rey-Caramés et al., 2015), or ground-based sensors (Bourgeon et al., 2017), have been widely employed to evaluate canopy growth and vigor in commercial vineyards. According to the values of these spectral indices, segmentation of vineyard plots into different vigor zones has driven differential management procedures and selective harvesting.

Soil electrical resistivity (ER) measures the soil's property to oppose the flow of electrical current and is therefore related to soil water and ionic contents. ER (or its inverse, electrical conductivity, EC) is now being used in vineyards as a proxy for soil physical and chemical properties (Samouëlian et al., 2005), among them soil moisture and water holding capacity. Continuous resistivity/conductivity sensors currently available on the market can be grouped into the noninvasive electromagnetic induction systems (EMI sensors) and the invasive electrode-based direct current (DC) resistivity sensors. Both types have advantages and drawbacks that have to be considered (Sudduth et al., 2003).

A complete review of the capabilities of EC to understand soil-plant-water relationships and to define homogeneous water zones in vineyards can be found in Yu and Kurtural (2020).

Unlike fruit tree orchards, smart irrigation approaches, such as zone irrigation management (ZIM) or variable rate irrigation (VRI), are not yet extensively applied in vineyards. Still, some examples of their benefits toward increasing sustainability in grape growing can be found.

Use case no. 1: Balafoutis et al. (2017) evaluated the impact of the application of precision viticulture practices (during three consecutive seasons), namely, variable rate fertilization and ZIM, using the life cycle assessment (LCA) approach in two *Vitis vinifera* L. (cv. Syrah and Sauvignon blanc) vineyards sited in Greece. To establish the different zones within the two plots, soil electrical conductivity (EC) mapping (EC measurements were taken using EM-38 probe), assisted by elevation mapping using RTK-GPS, was used. In each plot, two homogeneous zones were delineated, and for each zone, irrigation volumes per zone were estimated as a fraction of actual evapotranspiration (ETa). ETa was calculated from ET estimated using a water balance model, which employed meteorological data acquired with an automatic weather station installed inside the vineyards and vigor measurements (Normalized Difference Vegetation Index (NDVI)) obtained from satellite imagery. In comparison to conventional management, the same Sauvignon blanc vineyard utilized ~17% less amount of water as a result of ZIM, and this reduction in the number of irrigation events and quantities contributed to a reduction of greenhouse gas (GHG) emissions from 212.9 Kg CO_2 eq/t grapes to 173.4 Kg CO_2 eq/t grapes, which reduces 18.5%.

Use case no. 2: Bellvert et al. (2021) evaluated the performance of an integrated methodology—based on a vine water consumption model and free-of-charge satellite imagery data—to optimize the precision irrigation (PI) of a 100 ha commercial vineyard during two consecutive seasons. Using an NDVI-generated map, a vineyard with 52 irrigation sectors and 3 *Vitis vinifera* L. cultivars (Tempranillo, Cabernet Sauvignon, and Syrah) was grouped into 3 vigor levels (low, medium, and high), and different, precise regulated deficit irrigation (RDI) strategies were adopted by growers. The adoption of precision irrigation led to a reduction of water volumes which ranged from 14% to 38% depending on the year and energy and water cost savings as high as 35% and 53%, respectively, as compared to a conventional irrigation strategy.

As future implementations toward smart, more sustainable vineyard irrigation, advancements in big data, artificial intelligence, and data analytics, as well as their combination with Internet of Things (IoT) solutions, are proposed (Abioye et al., 2020). Moreover, the integration of evolutional algorithms for the parameter adjustment of adaptive irrigation controllers and the development of innovative digital irrigation technologies are also meant to foster the wide adoption of smart irrigation strategies.

4.7 Conclusions

Humans have been growing grapes for millennia. The grapevine is a drought-tolerant species, but its water requirements are very high. Irrigated vineyards are increasing on the surface worldwide, and water availability is decreasing, particularly aggravated by climate change. Therefore, viticulture sustainability will depend on precise, smart water management. A wide range of manual or automated sensors and technologies are currently available or under development to provide reliable and frequent information about water status variability in vineyards that can be adopted by viticulturists to drive better and more informed decisions about irrigation scheduling. This chapter aims to provide a comprehensive review of current and prospective tools to the relevant stakeholders that steer water usage in the grape and wine industry to minimize the existing breach between technological solutions and models and grape growers.

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Chapter 5
Pest and Disease Management

Won Suk Lee and Javier Tardaguila

Abstract This chapter describes the current sensing and actuation technologies for pests and plant diseases in orchards and vineyards. The technologies for pests include machine vision and imaging, trapping, data mining, nuclear magnetic resonance (NMR), DNA analysis, landscape and soil management, vibrational signals, precision spraying, and bird control. Some new technologies for pests were developed, such as predicting future infestation using artificial intelligence and pest identification using smartphone apps; however, more efforts will still be needed. The technologies utilized in plant disease detection and management include computer vision, thermography, spectroscopy, chlorophyll fluorescence, multi- and hyperspectral imaging, plant volatile organic compounds, biosensors, sensing platforms and robots, and artificial intelligence. Overall, new, reliable, easy-to-use, and objective methods will still be needed, along with continued support and interest from growers and industries.

5.1 Orchard and Vineyard Management for Pests and Diseases

Modern and sustainable agriculture requires objective and continuous monitoring of the crop. New technologies, sensors, artificial intelligence, and automation will play a more significant role in the agriculture of the future. Today, there is a wide range of new technologies whose use in monitoring crops has provided us with objective, robust, and reliable results. Subsequently, after an objective and reliable diagnosis

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of the vineyards and tree fruit orchards, we need to take action to optimize the management of pests and diseases. Efficient management of agricultural diseases and pests is crucial for eventually increasing crop yield and profit.

Agricultural pests are defined as “organisms that diminish the value of resources in which man is interested. They interfere with the production and utilization of crops and livestock used for food and fiber” (USDA ERS, 1999). They include “all noxious and damaging organisms: insects, mites, nematodes, plant pathogens, weeds, and vertebrates.” This chapter is focused on insects, mites, nematodes, and vertebrates.

Common insect pests in orchards are apple maggot, brown marmorated stink bug, codling moth, leafrollers, spider mites, spotted wing drosophila, and woolly apple aphid (Beers et al., 1993). The major arthropod pests in vineyards are phytophagous mites, phylloxera, leafhoppers, mealybugs, and grape berry moths (Bostanian et al., 2012). For citrus production, common insects are Asian citrus psyllid, citrus leaf miner, citrus root weevils, citrus rust mites, spider mites, Caribbean fruit fly, and thrips (Diepenbrock et al., 2019a, b; Duncan & Mannion, 2019; Qureshi et al., 2019).

Most insect pests are controlled by cultural, biological, physical, semiochemical, and chemical controls (Bostanian et al., 2012). They emphasized that “the main challenge for integrated pest management remains the development and coordination of all information and technologies into an optimally relevant package to growers in a given area.” Some new technologies were reported for site-specific viticulture (Tisseyre et al., 2007). The technologies included georeferencing information, equipment, and people and yield monitoring, in-vineyard quality monitoring, canopy and vigor monitoring, soil monitoring, water stress monitoring, and variable rate technology. They provided some example management practices for spatial and temporal variabilities. For non-pesticide management, Wilson and Daane (2017) reviewed ecological approaches for pest management in California vineyards. The methods included mating interruption, ant control for mealybugs, habitat management, natural enemy augmentation, animal integration, and biodynamic preparations. They emphasized that these practices should be “reliable and affordable” to growers for wide adoption.

Fungi, bacteria, mycoplasmas, and viruses can cause important diseases in crops. Infected plants usually show different visual and typical symptoms in different organs such as stems, leaves, and fruits; however, some plant infections can be symptomless, mainly in the early infection stages of the infection (Fig. 5.1).

Diseases can negatively affect the yield and quality of the fruit trees and can even induce the death of the plant. Crop diseases cause significant economic losses in agricultural production over the world. The environmental and economic impacts of crop protection are significant (Pimentel et al., 2005). A major impact is caused when the plant develops when the infection occurs. Plant pathogen detection is important as the first step in crop protection in agriculture. An early pathogen detection system can decrease such losses caused by plant diseases and reduce the spread of diseases (Mahlein, 2016; Mahlein et al., 2018, 2019; Thomas et al., 2018).

Fig. 5.1 Commercial vineyard infected by grapevine trunk diseases (GTD). Visual symptoms in leaves, shoots, and clusters are shown. Asymptomatic leaves were observed. (Photo: Javier Tardaguila)

This chapter presents principles, methods, and hardware and software technologies to detect, classify, and quantify pests and diseases. It also discusses state-of-the-art and emerging actuation technologies for targeted control of pests and diseases using ground and aerial platforms.

5.2 Sensing and Actuation Technologies for Pests

5.2.1 State-of-the-Art Sensing and Actuation Technologies for Pests

Pests are one of the main problems in crop production. Efficient and effective pest management is crucial for increasing yield and profit. Many different technologies have been used for pest infestation and crop damage to achieve this goal.

5.2.1.1 Machine Vision and Imaging Technologies

One of the most common methods for pest detection is machine vision, including multispectral and hyperspectral imaging. Image-based insect detection methods were developed to identify eight insect species. A correct classification rate of 87% was reported (Wen & Guyer, 2012), using various features such as geometry, contour, texture, and color. Another study (Hassan et al., 2014) also utilized color and shape features and a support vector machine (SVM) classifier to develop an automatic insect classification method for grasshoppers and butterflies as examples. They reported 92% detection accuracy. Machine vision algorithms could be used for autonomous selective pesticide spraying in vineyards (Berenstein et al., 2010), which reported a 30% reduction of applied pesticide agents.

Some study was conducted to identify spectral characteristics of insect pest infestation. Using reflectance measurement of infested leaves, Blanchfield et al. (2006) investigated an indirect method for detecting phylloxera infestation through leaf pigment composition. They reported a reduction of leaf chlorophyll and an increase in photoprotective pigment concentrations due to phylloxera infestation. Spectral measurement was also used for detecting damages by nematodes, even though the study was conducted for cotton (Lawrence et al., 2007) or sugar beet (Hillnhütter et al., 2011).

For machine vision applications, multispectral and hyperspectral imaging is commonly used. One such study was conducted by Benheim et al. (2012). They implemented multispectral and hyperspectral imaging to detect phylloxera infestation in vineyards. They reported that these imaging methods had some potential. However, they might not be able to detect the infestation since many other factors were showing similar spectral signatures, such as water stress or nitrogen deficiency. They pointed out that soil temperature, moisture content, salinity, and apparent electrical conductivity were highly correlated with the establishment and distribution of phylloxera.

UAV is also commonly used for orchard and vineyard pest management. Vanegas et al. (2018) utilized various cameras installed on a UAV to detect different levels of grape phylloxera infestation. Airborne color, multispectral, and hyperspectral images were acquired from two phylloxera-infested vineyards in Victoria, Australia. Color images and various vegetation indices were used to determine infestation levels.

Even though for other crops such as strawberries or soybean, a color image processing algorithm was implemented to detect thrips (Thysanoptera) for greenhouse strawberries (Ebrahimi et al., 2017). Combined with a support vector machine (SVM) classifier, they could correctly detect thrips with a mean detection error of 2.3% using 20 testing images. Hyperspectral transmittance images were used to detect insect-damaged vegetable soybean (Huang et al., 2013). These methods could be applied to crops in orchards and vineyards.

Electrical conductivity (EC) was used along with imaging (Bruce et al., 2009). Early detection of grapevine phylloxera was investigated using traps, soil samples, electromagnetic surveys, aerial multispectral images, and a reflectance sensor (GreenSeeker). They found that soil EC and chemical analysis indicated a potential for early detection and reported more infestation in higher soil EC areas and high magnesium contents. They described that remote sensing techniques should be able to distinguish symptoms from other stress factors, contrary to Benheim et al. (2012).

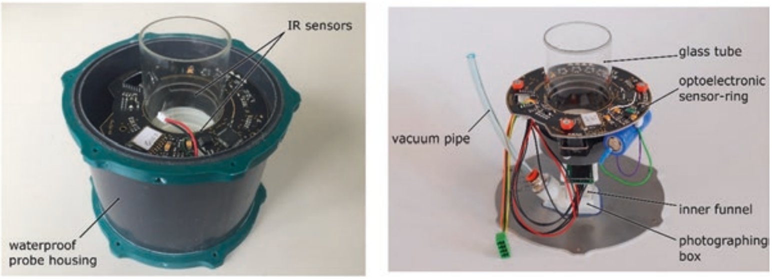

Fig. 5.2 Camera-supported trapping probe for detecting soil microarthropods with protecting tube (left) and without it (right). (Adapted from Florian et al. 2020)

Multispectral imaging also was used for nematode detection. Even for another crop (soybean), Kulkarni et al. (2008) utilized aerial four-band multispectral imaging to identify nematode population density. There was a potential for remote sensing and some difficulties due to the complicated relationship between soil nematode population and crop damage.

5.2.1.2 Trapping

Trapping is another method to detect insect pests. Hillier and Lefebvre (2012) used pheromone trapping to detect insect pests in vineyards. Renkema et al. (2014) developed a plastic jar trap for *Drosophila suzukii* and compared it with commercial traps for trapping performance. They reported some results related to trapping entry size, colors, the existence of holes, attractant volumes, headspace volume, replacement frequency, etc. More recently, Florian et al. (2020) developed a trap with an optoelectronic ring and camera for detecting soil microarthropods such as springtails (Collembola), mites (Acari), coleopterans (Coleoptera), dipteran larvae (Diptera), isopods (Isopoda), and diplopods (Diplopoda). The proposed trapping probe is shown in Fig. 5.2. Their success rate was 60–70%.

5.2.1.3 Data Mining

Tripathy et al. (2011) implemented a wireless sensor network and data mining techniques to identify relationships between pest insect (thrips) infestation and weather conditions. Using the naïve Bayes algorithm and rapid association rule mining, they identified a correlation between weather data and pest infestation and developed a multivariate regression model which can predict insect establishment and degree of infestation.

5.2.1.4 Nuclear Magnetic Resonance (NMR)

Tucker et al. (2007) used nuclear magnetic resonance (NMR) spectroscopy to detect phylloxera in grapevine leaves. Infested leaves showed metabolic changes, and their extracts, such as unsaturated fatty acids, exhibited infestation markers, even though very similar to nitrogen stress.

5.2.1.5 DNA Analysis

DNA analysis was also used. Bruce et al. (2011) integrated phylloxera-specific DNA analysis from grid soil samples with their previous study. They reported that soil-based DNA assays have the potential to detect phylloxera; however, more evaluation would be needed.

5.2.1.6 Landscape Elements and Soil Management

Landscape elements were used for insect pest management. Judt et al. (2019) investigated the effect of landscape elements and inter-row management on the arthropod populations using 15 commercial vineyards in Andalusia, Spain. The landscape elements included semi-natural vegetation, olive orchards, vineyards, and other agricultural areas. The inter-row management included vegetation cover and bare soil. The number of arthropods decreased when there were other surrounding vineyards. Also, they reported that semi-natural and olive orchards didn't affect the arthropods' population but found more arthropods from inter-row vegetation and more spiders from bare soil. These findings suggested integration of local landscape structure and inter-row management should be considered for more effective pest management.

Soil management affects insect pest infestation. Sáenz-Romo et al. (2019) studied the effects of soil management techniques (tillage, spontaneous cover, and flower-driven cover) on insect predators and pests in Mediterranean vineyards. Relative abundance (%), defined as the "proportion of collected insects from each study's taxa of the total number," was used to compare the effect by ANOVA. They found that the cover crop vegetation increased beneficial insects such as carabids and forficulids. The spontaneous cover vegetation increased the abundance of ground beetles and the carnivorous genus *Nebria*, indicating management of spontaneous cover vegetation is the most important for conservation biological control.

5.2.1.7 Vibrational Signals

Korinsek et al. (2016) proposed one unique approach for pest control, which used species- and sex-specific substrate-borne vibrational signals. They analyzed the male and female leafhopper mating calls and proved the concept of using the audio signal for developing an insect trap.

5.2.1.8 Precision Spraying

Many studies were conducted for precision chemical spraying for efficient insect pest control. Kang et al. (2011) developed a laser-based trunk size detection system to precisely spray barriers for cutworms in vineyards. A 40 Hz laser sensor was installed on both sides of a small trailer with three different nozzles to achieve variable rates depending on the trunk size. In a field trial, they reported about 5 mm error in trunk radius estimation at five different travel speeds and average targeted spray efficiencies of 65–71% with 90–91% cost savings compared to typical application.

Escola et al. (2013) developed a variable rate sprayer using a LiDAR sensor for canopy volume measurement, a controller for determining spray rates, and electromagnetic variable valves as actuators for tree fruit orchards. They compared the algorithm determined and actual spray rates and found a strong relationship with a coefficient of determination of 0.94.

Gil et al. (2013) developed a similar variable rate sprayer using ultrasonic sensors, variable rate electro valves, and a controller for vineyards. They tested the sprayer at Merlot and Cabernet Sauvignon vineyards and reported a good relationship between the algorithm determined and actual spray rates and 22% savings compared to a conventional application.

Adamides et al. (2014) investigated different interaction interfaces for a teleoperated vineyard sprayer tested by 30 different human operators. They tested a single camera and multiple camera systems and found that the multiple view system was more efficient in spraying and yielded fewer collisions with various obstacles but took more time to complete tasks than a single camera system. Further, Adamides et al. (2017) developed a semi-autonomous vineyard sprayer and investigated the human interface with a robotic system.

Using plant cell density (PCD, a ratio of near-infrared band over a red band), Roman et al. (2020) compared variable pesticide application rates in vineyards. They calculated the PCD from airborne multispectral images, used to estimate plant vigor and application rates. They reported pesticide savings of more than 25% compared to standard treatment.

Li et al. (2009) constructed an automatic sprayer for insects using binocular stereo-vision constructed from a single camera for other crops. In a laboratory environment, the system scanned sample plants from bottom to top to identify the location of artificial insects using depth information and sprayed them. However, no test results regarding spraying performance were reported in the study. Further, Li et al. (2015) utilized multifractals, defined as "an extension of fractals with multiple scales," to identify small-sized insects like whiteflies in greenhouses. From their testing with paprika plants in a greenhouse, their proposed method yielded 87% of correct detection.

5.2.1.9 Bird Control

Bird control is another important aspect of pest control for orchards and vineyards.

Ampatzidis et al. (2015) developed an autonomous bird control system using UAVs, a wireless ground sensor network, wearable devices, and a cloud-based decision system. The system posed visual (with large size drone), audio (unique sound), and chemical (target spraying of methyl anthranilate, a bird irritant) threats to pest birds. Even though they simulated bird detection events, the developed system successfully created UAV flight paths to bird location, spot-sprayed chemicals, and turned on speakers autonomously. They pointed out that short flight time, insufficient sprayer size, chemical efficiency, and bird detection accuracy could be potential problems.

A multilayer artificial neural network was utilized to detect pest birds in vineyards (Dolezel et al., 2016). Their study focused on a few representative species to be more effective. Previously recorded sound of birds was used to identify the presence of a target bird using labeled features by the linear prediction coding (LPC) as input vectors of the neural network. They reported 89% detection accuracy for the European starling (*Sturnus vulgaris*) and emphasized that the network would be suitable for field implementation since it does not require high computing power.

Another study was conducted for pest bird control. Bhusal et al. (2017) developed a bird detection system for wine grapes using outdoor cameras installed at four corners of a field and a Gaussian mixture-based segmentation algorithm. The most common problem birds in wine grapes were starlings, robins, and finches. Bird tracking was implemented using the Kalman filter. They reported an 85% precision in detecting and counting birds in a 30 m × 30 m testing plot by comparing manual and algorithm counts. They reported that shape features were not very useful due to distortion by motion blurriness. They counted 89 incoming and 46 outgoing birds during 2 h in the morning in 6 days.

Then, Bhusal et al. (2018) implemented unmanned aerial vehicles (UAVs) in a 15,000 m^2 (about 3.8 acres) commercial vineyard to keep away birds (starlings and robins). They tested the system over 14 days with a 5-hour flight each day. Two UAVs (Matrice M600 Pro and Phantom 4, DJI Inc., China) were flown 3–6 m above the canopies. Using ANOVA, they compared the effectiveness of flying UAVs relative to when no drones were used and found a significant difference in the number of birds when UAVs were used (about 50% less number of birds). Their future study included detecting incoming birds and redirecting them away from the vineyards.

Further, Bhusal et al. (2019) adopted the convolutional neural network (CNN) using very high 4 K resolution images (3840 × 2160 pixels) to enhance bird detection. They observed that classification accuracy increased from 70% to 92% using super-resolution images, but a more reliable model would be needed.

5.2.1.10 Summary

In summary, various methods were used to detect and control pests in orchards and vineyards. Most of the methods focused on detecting and managing insect pests. More efforts will be needed to develop sensing technologies for other pests such as mites, nematodes, and vertebrates. More research and field experiments will be needed for actual field implementation by growers.

5.2.2 Emerging Technologies for Pests

Based on the National Grape Research Alliance (https://graperesearch.org/), some of their top research priorities are building improved mechanization and automation systems to enhance labor efficiency and improve pest and disease detection, modeling, and control systems. However, as Rieger (2019) reported, most vineyard sensing technologies are currently focused on meteorological and soil conditions and water status for irrigation. He also reported that machine learning and artificial intelligence (AI) are heavily used to assess data and develop decision support models.

Some studies for insect pest detection use traditional artificial neural networks (Fedor et al., 2009); however, the current explosion of AI applications started with AlexNet, developed by Krizhevsky et al. (2012). AI has been used to detect insect pests (Ding & Graham, 2016; Shen et al., 2018; Xia et al., 2018) and can be used to predict future infestation. Among many studies, Nam and Hung (2018) compared the performance of VGG16 and SSD (single-shot multibox detector) for detecting insects on sticky traps and found that SSD was better for identifying insects.

More recently, instead of manual crop scouting in citrus production, an automated insect detection system was developed using machine vision and AI for the Asian citrus psyllid (ACP), which is the vector of the devastating Huanglongbing (or citrus greening) disease for citrus (Partel et al., 2019). By implementing pneumatic tapping rods, as shown in Fig. 5.3, images of insects collected on a viewing board were acquired and were analyzed by two consecutive convolutional neural networks (YOLO v3 and then YOLO v1) to increase detection accuracy. After testing on 90 citrus trees, precision (accuracy) and recall (sensitiveness) were reported to be 80% and 95%, respectively.

Along with the development of mobile AI, smartphone apps will be available in the near future. Schumann et al. (2020) reported an accuracy of 89% for identifying pests, disease, and nutrient deficiencies using a smartphone app trained by a deep neural network. However, they noted that it would not replace traditional diagnostic lab methods soon. A startup company, Bloomfield Robotics (https://bloomfield.ai/), is developing a mobile sensor platform and implementing AI and robotics in vineyard management for monitoring vine growth and berry yield. Another company (Vayyar Ltd., Israel) seems to be of interest to us, which developed a sensor that can create high-resolution 3D images by measuring the radiofrequency reflectance of objects. Niu et al. (2020) utilized the sensor to detect nematodes in walnut leaves and reported a 72% accuracy for classifying nematode infestation levels.

An attempt has been made to replace high spatial resolution UAV images with satellite images for managing a vineyard. In a recent study by Sozzi et al. (2020), NDVI from two different imaging platforms, i.e., Sentinel-2 satellite and UAV, were compared for precision vineyard management. Images were acquired from 30 vineyards in France, and the spatial resolution was the same as 10 m for both Sentinel-2 and UAV (upscaled from its original 0.08 m). Sentinel-2 images detected the same degree of variability when no individual vine management is needed, and no inter-row grass is used in NDVI calculation.

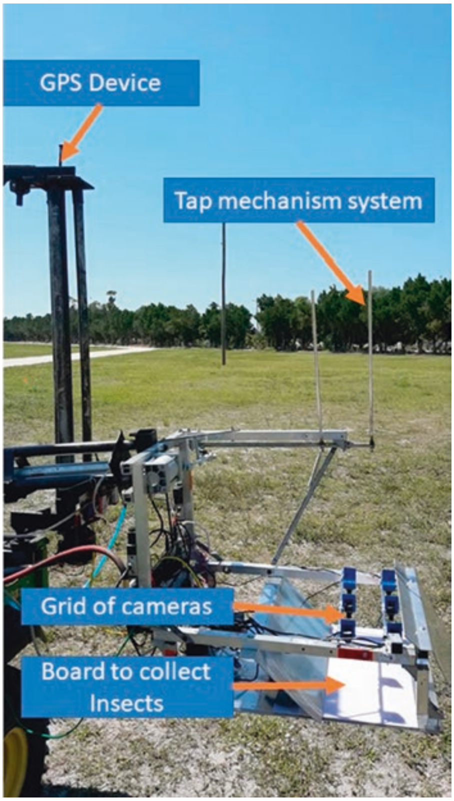

Fig. 5.3 Automated insect (Asian citrus psyllid) detection system. (Adapted from Partel et al., 2019)

A new integrated pest management (IPM) model (Fig. 5.4) was proposed by Dara (2019), which includes management, business, and sustainability aspects. The management aspect includes pest management, knowledge, resources for pest and technology, planning and data organization, communication among growers and the public, and research and outreach. In the business aspect, public education was emphasized for efficient IPM and traditional training for growers. In the sustainability aspect, conventional farming can be safer and more sustainable as long as IPM principles are emphasized, rather than organic farming, which is traditionally considered safe but can cause some "social inequality and a false sense of well-being."

A more precise spraying system was developed using a laser. Chen et al. (2019) tested a laser-guided intelligent sprayer in tree crop nurseries to investigate the efficiency of controlling insects and diseases. They found 52–56% of pesticide reduction and equal or a smaller number of insects (leafhoppers and aphids). A commercial sprayer is already available using this technology.

In predicting pest infestation, spatial interpolation using GIS and machine learning can be useful tools. While describing the IPM of mites, Liburd et al. (2019)

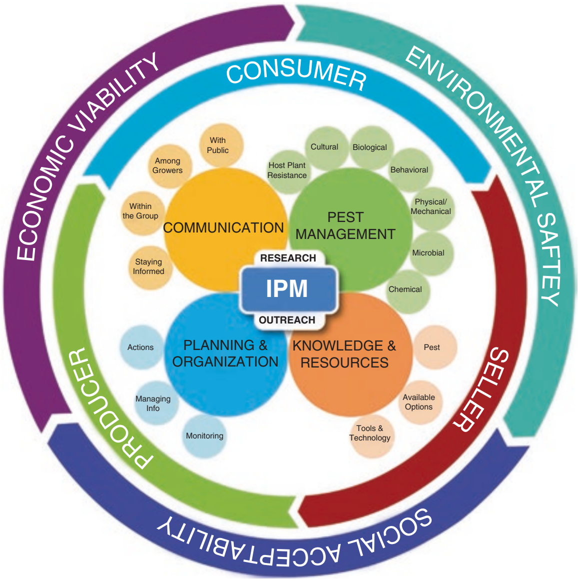

Fig. 5.4 A new model for integrated pest management. (Adapted from Dara, 2019)

suggested spatial interpolation of pest density using GIS to predict pests at unsampled locations in a field. This information can be used for site-specific spot spraying of insecticides. They expected that machine learning could be useful for identifying the distribution and infestation of pests and predatory insect species.

Overall, some new technologies have been developed and are currently being investigated for fruit orchards and vineyards. With more interest and support from growers, industries, and state and federal agencies, more effort will still be needed for pest detection and management.

5.3 Sensing and Actuation Technologies for Plant Diseases

Advanced technologies can also be applied for detecting plant diseases in agriculture with several advantages versus conventional methods. Emerging technologies can be used for quantitative and qualitative evaluation of plant diseases (Ali et al., 2019; Mahlein et al., 2018, 2019; Ray et al., 2017; Sankaran et al., 2010).

Visual symptoms of infected plants can be evaluated by optical sensors directly in the field using computer vision sensors mounted on the ground and aerial platforms. However, visual symptoms assessment is a conventional first step for plant disease diagnosis. Still, it fails to detect a pathogen in early infection stages when plant infections are asymptomatic. Early detection of plant pathogens can be very important for crop health monitoring. It allows for optimized crop protection in the field during different stages and minimizes the risk of the spread of disease infections and reduces spray treatments. Indeed, early detection of plant disease is needed in agriculture to reduce the economic and environmental impact. Hyperspectral sensors are shown as one of the most powerful technologies for early disease detection in agriculture (Mahlein et al., 2018, 2019; Thomas et al., 2018). Moreover, machine learning and recently deep learning have been successfully developed and applied in phytopathology to make a prediction from data and to improve the decision-making process in crop protection (Zhu et al., 2017; Mahlein et al., 2019; Polder et al., 2019; Sladojevic et al., 2016) in the context of precision farming.

5.3.1 State-of-the-Art Sensing and Actuation Technologies for Plant Diseases

In agriculture, diseases in plants are typically verified using several conventional methods. Traditionally, plant disease incidence is assessed by the interpretation of visual symptoms. Visual assessment and culturing are subjective methods and require trained personnel and considerable time to complete a diagnosis. Other current and conventional methods were based on the laboratory analysis of samples collected in the field, manually at a single plant. Enzyme-linked immunosorbent assays (ELISA), immunology-based methods, polymerase chain reaction (PCR), and real-time PCR (RT-PCR) can be used for plant disease detection (Fang & Ramasamy, 2015; Ray et al., 2017). These methods are time-consuming and require complex and expensive instruments, which are not appropriate for infield operation. A summary of the advantages and limitations of these methods is shown in Table 5.1. All these lab methods were precise with high accuracy for plant pathology diagnosis; however, they required collecting plant samples before wet chemistry analysis, limiting their infield applications. Consequently, there is strong interest in developing new and reliable technologies for plant disease detection under field conditions.

Table 5.1 Current and conventional methods in plant disease detection

Method	Advantages	Limitations
Visual assessment	Easy to operate	Subjective Time-consuming Trained personnel
Culturing methods	Cheap and simple	Non-rapid Subjective Trained personnel
Isoenzyme analysis	Precise and rapid	Low level of polymorphism in fungi Not suitable for infield operation
Immunology-based methods	Accurate	Low sensitivity Not suitable for infield operation
Polymerase chain reaction (PCR)	High accuracy and sensitivity	Expensive Not suitable for infield operation

The above methods for plant disease detection have been mainly applied in research, breeding, and phenotyping; however, they are not suitable for infield operation. The applications of these lab methods in commercial agriculture have been limited. Currently, new techniques for rapidly and cost-effectively assessing diseases in vineyards and fruit orchards are needed.

5.3.2 Emerging Technologies for Plant Diseases

New sensors and technologies can be used to evaluate crop status quickly and inexpensively. New technologies can assess plant diseases with reliability, precision, and accuracy (Mahlein, 2016; Mahlein et al., 2018, 2019; Ray et al., 2017; Sankaran et al., 2010). It is important to emphasize that the non-destructive nature of many of these technologies implies the absence of damage or any modification of the plant material under analysis. Some of the main non-invasive detection technologies used for crop monitoring include computer vision, thermography, spectroscopy, chlorophyll fluorescence, and multi- and hyperspectral imaging.

These sensing technologies can be implemented in portable sensors. However, they can also be mounted on vehicles such as quads, tractors, or robots and even aerial platforms such as drones, aircraft, or satellites. Proximal and remote sensing technologies are playing an increasingly prominent role in modern agriculture, making it easier to gather data quickly and affordably. Furthermore, the new and powerful non-invasive sensors can obtain georeferenced information in most cases. It is possible to generate maps of the different parameters and establish zones that require different management practices within precision agriculture.

5.3.2.1 Plant Volatile Organic Compounds

Recently, it was suggested that plant volatile organic compounds could be used in agriculture to improve crop defense strategies (Brilli et al., 2019). The pathogen-plant interaction could result in the release of specific volatile organic compounds that highly indicate the plant disease (Fang et al., 2014; Fang & Ramasamy, 2015; Ray et al., 2017). Gas chromatography combined with mass spectroscopy has been used for analyzing volatile organic compounds emitted by diseased plants (Fang & Ramasamy, 2015). However, before analyzing the volatile compounds by gas chromatography, several complex strategies and procedures for obtaining these volatile compounds from a single plant should be defined and performed (Tholl et al., 2006). This technique has been used for detecting fungal diseases in various plants (Fang et al., 2014; Vikram et al., 2006).

Nowadays, plant volatile compound analysis is time-consuming and requires a pre-sampling manually in the field, so infield application was very limited. Several recent reviews have discussed the different strategies for monitoring volatile compounds for plant disease detection (Sankaran et al., 2010; Fang & Ramasamy, 2015; Martinelli et al., 2015).

5.3.2.2 Biosensors

Biosensors are a novel diagnostic tool for detecting plant diseases. On-site detection of plant pathogens can be performed using biosensors. Integration of different techniques in portable devices led to the development of biosensors. Table 5.2 summarizes the main biosensors used to detect numerous fungal pathogens. Biosensors used in plant disease detection have been recently reviewed by Ray et al. (2017). Biosensors are gaining much interest for detecting fungal plant diseases and can be a promising alternative tool in crop protection. Some recent reviews have described the strategies of the different biosensors for detecting plant diseases (Ray et al., 2017; Khater et al., 2017). Several biosensors based on different techniques are commercially available to detect several plant pathogens such as *Phytophthora*, *Pythium*, *Oidium*, and *Botrytis cinerea* (Ray et al., 2017; Khater et al., 2017). Commercial biosensors are portable small/pocket devices for detecting diseases at the leaf or plant level, and they can be used under lab or field conditions (Khater et al. 2017).

Table 5.2 Main biosensors used in plant fungal pathogen detection

Type of method	Biosensor	Pathogen
Optical biosensors	Fluorescence-based biosensors	*Phytophthora palmivora*
	Chemiluminescence-based biosensors	*Saccharomyces cerevisiae* *Hansenula anomala*
	Surface plasmon resonance (SPR)-based biosensors	*Phytophthora infestans*
Volatile biosensors	Electronic nose system	*Botrytis* sp. *Penicillium* sp.
	Field asymmetric ion mobility spectrometry (FAIMS)	*Oidium neolycopersici*
Electrochemical biosensors	Amperometric platform	*Saccharomyces cerevisiae* *Cerrena unicolor*
	Potentiometric platform	*Lentinus sajor-caju*
	Impedimetric platform	*Phakopsora pachyrhizi* *Penicillium sclerotigenum*
	Conductometric platform	*Candida albicans*, *Aspergillus niger*
Mass-sensitive biosensors	Quartz crystal microbalance (QCM) biosensors	*Candida albicans* *Candida glabrata*
	Cantilever-based biosensors	*Aspergillus niger* *Saccharomyces cerevisiae*
Point-of-care (POC) tests	Lateral flow assays (LFAs)	*Phytophthora* species
	Microfluidic paper-based analytical devices (μPADs)	*Botrytis cinerea* *Peronospora destructor*
Nanomaterial-based biosensors		*Aspergillus niger* *Metarhizium anisopliae*

Adapted from Ray et al. (2017)

5.3.2.3 Non-destructive/Non-invasive Sensing Technologies

Non-destructive/non-invasive sensing technologies are gaining much interest for detecting plant diseases and can be a promising alternative tool in crop protection. Non-destructive/non-invasive (both terms are interchanged, generally) techniques are defined as methods that do not alter the physical state of an object. These technologies have been successfully implemented to measure some important physiological parameters in non-invasive ways. Non-invasive sensing technologies are associated with remote and proximal sensing, which acquire information from the plant-pathogen interaction. Most of these technologies are based on the interaction between electromagnetic radiation and the plant. The electromagnetic spectrum provides information about plant physiological status, and consequently, an infected plant generally displays a different spectral signature to that of a healthy plant (Ali et al., 2019; Delalieux et al., 2007; Sankaran et al., 2010).

Non-destructive technologies used for detecting plant diseases were reviewed by several authors (Ali et al., 2019; Mahlein et al., 2018, 2019; Ray et al., 2017; Sankaran et al., 2010; Thomas et al., 2018). Table 5.3 summarizes non-invasive sensing technologies employed for detecting diseases in vineyards and tree fruit orchards. Non-invasive technologies include fluorescence, thermography, X-ray, spectroscopy, computer vision, multispectral imaging, and hyperspectral imaging. They were applied in grapevine, citrus, apple, pear, avocado, kiwifruit, raspberry, etc. Numerous important crop pathogens and diseases such as citrus greening disease (Huanglongbing), citrus canker (*Xanthomonas citri*), apple scab (*Venturia inaequalis*), phytophthora root rot disease, downy mildew (*Plasmopara viticola*), powdery mildew (*Erysiphe necator*), *Botrytis cinerea*, Flavescence dorée, grapevine leafroll disease, and grapevine trunk diseases (GTD) were detected using non-invasive technologies.

Non-invasive sensing technologies can be integrated into portable devices and ground and aerial platforms, as discussed in the next section. Some technologies are commercially available for disease detection in grapevine and fruit trees, while others are being developed.

5.3.2.4 Hyperspectral Imaging

Hyperspectral imaging (HSI) is one of the most powerful non-invasive technologies. Hyperspectral imaging has been applied in agriculture, forestry, environment, defense, medicine, water, food quality, and safety control. Spectral resolution (narrower wavelengths) and the band number are the key features that characterize HSI. Hyperspectral imaging provides one full spectrum for each pixel of the collected image. Hyperspectral sensor and imaging techniques have shown a great potential for detecting plant diseases. Several authors have recently reviewed HSI applications in phytopathology (Mahlein et al., 2018, 2019; Thomas et al., 2018). Specific spectral indices can be developed for disease detection and monitoring in precision agriculture (Mahlein et al., 2013).

Table 5.3 Non-invasive sensing technologies for detecting diseases in apple trees, citrus, grapevine, and tree fruit plants

Technology	Plant	Disease/pathogen	References
Fluorescence	Citrus	Citrus canker (*Xanthomonas citri*)	Belasque et al. (2008) and Lins et al. (2009)
	Grapevine	Powdery mildew (*Erysiphe necator*) Downy mildew (*Plasmopara viticola*) Downy mildew (*Plasmopara viticola*)	Bélanger et al. (2008), Cséfalvay et al. (2009) and Latouche et al. (2015)
Thermography	Apple	Apple scab (*Venturia inaequalis*)	Oerke et al. (2011)
	Kiwifruit	Pseudomonas syringae pv. actinidiae (Psa)	Maes et al. (2014)
	Grapevine	Downy mildew (*Plasmopara viticola*)	Stoll et al. (2008)
	Olive tree	*Verticillium*	Calderón et al. (2013)
X-ray	Raspberry	*Botrytis cinerea*	Goodman et al. (1992)
	Grapevine	Grapevine trunk disease (GTD)	Vaz et al. (2012)
Spectroscopy	Apple	Apple scab (*Venturia inaequalis*)	Delalieux et al. (2007)
	Citrus	Anthracnose	Blasco et al. (2007)
	Grapevine	Grapevine leafroll disease Grapevine trunk disease (GTD)	Naidu et al. (2015) and Levasseur-Garcia et al. (2016)
Computer vision	Apple	Apple scab (*Venturia inaequalis*)	Wijekoon et al. (2008)
	Citrus	Anthracnose	Blasco et al. (2007)
	Grapefruit	Greasy spot (*Mycosphaerella citri*), melanose (*Diaporthe citri*), and scab (*Elsinoe fawcettii*)	Pydipati et al. (2006)
	Avocado	Phytophthora root rot disease	Salgadoe et al. (2018)
	Grapevine	Powdery mildew (*Erysiphe necator*)	Oberti et al. (2014)
Multispectral imaging	Citrus	Citrus greening disease (Huanglongbing)	Kumar et al. (2012)
	Grapevine	Grapevine leafroll disease (GLD) Flavescence dorée *Armillaria*	Hou et al. (2016) and Albetis et al. (2017) Candiago et al. (2015)
	Olive tree	*Verticillium*	Calderón et al. (2013)
Hyperspectral imaging	Apple	Apple rottenness (*Penicillium*)	Zhang et al. (2015)
	Pear	Pear black spot disease (*Alternaria alternata*)	Pan et al. (2019)
	Citrus	Citrus canker (*Xanthomonas citri*) Citrus greening disease (Huanglongbing) Citrus greening disease (Huanglongbing)	Qin et al. (2008), Lee et al. (2008) and Moriya et al. (2019)
	Grapevine	Downy mildew (*Plasmopara viticola*) Powdery mildew (*Erysiphe necator*)	Oerke et al. (2016) and Pérez-Roncal et al. (2020)

Table 5.4 Hyperspectral imaging (HSI) applications in grapevine and fruit tree orchards

Plant	Imaging conditions	Disease/pathogen	References
Citrus	Field	Citrus greening disease (Huanglongbing)	Moriya et al. (2019)
Pear	Laboratory	Pear black spot disease (*Alternaria alternata*)	Pan et al. (2019)
Apple	Laboratory	Apple rottenness (*Penicillium*)	Zhang et al. (2015)
Olive	Field	*Xylella fastidiosa*	Zarco-Tejada et al. (2018)
Grapevine	Laboratory	Downy mildew (*Plasmopara viticola*)	Oerke et al. (2016)
Grapevine	Laboratory/field	Downy mildew (*Plasmopara viticola*)	Poblete-Echeverría & Tardaguila, (2023)
Grapevine	Laboratory	Powdery mildew (*Erysiphe necator*)	Pérez-Roncal et al. (2020)

Table 5.4 summarizes HSI applications in grapevine and fruit tree orchards. HSI was employed in citrus, pear, apple, grapevine, etc. Several important plant pathogen diseases such as citrus greening disease (Huanglongbing), pear black spot disease (*Alternaria alternate*), apple rottenness (*Penicillium*), downy mildew (*Plasmopara viticola*), and powdery mildew (*Erysiphe necator*) were detected under laboratory and field conditions.

Hyperspectral imaging is a powerful technology, but it has been typically used under laboratory conditions. Very few attempts at infield hyperspectral imaging have been reported in the literature, due to the difficulties, such as natural and irregular illumination or unknown a priori sample positioning in the recorded scene, that are necessary to face.

Gutiérrez et al. (2018) have used HSI as a ground platform for grapevine phenotyping on the go. This study acquired hyperspectral images under natural illumination with a VIS-NIR hyperspectral camera (400–1000 nm) mounted on an all-terrain vehicle moving at 5 km/h in a commercial Tempranillo vineyard in Spain (Fig. 5.5). The same mobile hyperspectral sensing ground platform could be used for disease detection in commercial vineyards (Tardaguila et al. unpublished data). HSI sensor was also mounted into aircraft for detecting citrus greening disease (Huanglongbing) in Brazil (Moriya et al., 2019). *Xylella fastidiosa*, one of the most dangerous plant pathogens, was detected at the previsual stage in the olive orchard by hyperspectral and thermal sensors mounted in an airborne (Zarco-Tejada et al., 2018).

5.3.2.5 Sensing Platforms and Robots

Plant disease detection could be performed by integrating non-invasive sensing technologies into different platforms: portable devices (apps, smartphones, etc.), ground platforms (quads, tractors, robots, etc.), and aerial platforms (drones, aircraft, etc.) and satellites. Emerging technologies can be used for quantitative and qualitative evaluation of plant diseases (Ali et al., 2019; Mahlein et al., 2019; Ray

Fig. 5.5 Hyperspectral imaging camera mounted on an all-terrain vehicle moving at 5 km/h used for monitoring a commercial vineyard in Spain. (Photo: Javier Tardaguila)

Table 5.5 Sensing platforms for detecting diseases in vineyards and tree fruit orchards under field conditions

Platform	Plant	Disease/pathogen	References
Portable	Avocado tree	Phytophthora root rot	Salgadoe et al. (2018)
Ground platforms	Grapevine	Downy mildew Grapevine trunk diseases (GTD)	Tardaguila et al. (unpublished data)
Drone/UAV	Grapevine Grapevine Grapevine Citrus	Flavescence dorée Grapevine trunk diseases (GTD) *Armillaria* Citrus greening disease (Huanglongbing)	Albetis et al. (2017) Albetis et al. (2019) Candiago et al. (2015) and Garcia-Ruiz et al. (2013)
Aircrafts	Olive Citrus Citrus	*Xylella fastidiosa* Citrus greening disease (Huanglongbing) Citrus greening disease (Huanglongbing)	Zarco-Tejada et al. (2018) Garcia-Ruiz et al. (2013) and Moriya et al. (2019)
Satellites	Citrus	Citrus greening disease (Huanglongbing)	Li et al. (2015)

et al., 2017; Sankaran et al., 2010). The potential of aerial platforms to evaluate biotic and abiotic stress factors in precision agriculture has been recently reviewed (Sankaran et al., 2015). Table 5.5 summarizes sensing platforms that have been used for disease detection in vineyards and tree fruit orchards.

Phytophthora root rot incidence was assessed in an avocado orchard using RGB images taken by a smartphone camera. Visual symptoms of downy mildew and grapevine trunk diseases (GTD) in commercial vineyards were evaluated and mapped using an RGB sensor mounted on a mobile sensing platform at 5 km/h (Tardaguila et al. unpublished data).

Several diseases were detected in vineyards and citrus orchards using different remote sensing technologies integrated on aerial platforms such as drones or UAVs (Albetis et al., 2017; Albetis et al., 2019; Candiago et al., 2015; Garcia-Ruiz et al. 2013) and aircraft (Garcia-Ruiz et al., 2013; Moriya et al., 2019; Zarco-Tejada et al., 2018). Additionally, citrus greening disease (Huanglongbing) was detected using multispectral satellite information (Li et al., 2015).

The development and use of robotics can greatly facilitate the application of precision crop protection in the future, as it makes autonomous and continuous surveillance of the vineyards and orchards possible and optimizes any subsequent automated intervention based on the information obtained.

Sensing platforms offer the potential to map disease incidence in the plot. It can allow differential fungicide application using variable-rate technology. These new technologies will improve sprays' timing and volume, reducing agronomical damage, economic losses, and environmental impact.

5.3.2.6 Artificial Intelligence for Crop Protection

New technologies, sensor systems, artificial intelligence, and automation will be the key to the agriculture of the future. Artificial intelligence is a revolution at different work and industrial levels to deal with data. Machine learning has evolved greatly within artificial intelligence during the last decades, providing tools to make computers learn. These algorithms are used in many fields due to their high versatility for any data-related tasks, generating knowledge and information, and improving the decision-making process (Gutiérrez, 2019).

Advances in non-invasive sensing technologies allow the acquisition of high amounts of data from the vineyard. Still, these data alone are not enough to be used when decisions need to be made, and they need to be transformed into actionable information. Therefore, the combination of non-invasive sensors and artificial intelligence needs to be applied to meet the requirements needed to apply digital agriculture and data-driven agriculture.

Data are the key to disease diagnosis and decision-making in vineyards and fruit orchards (Mahlein, 2016; Mahlein et al., 2019). Artificial intelligence, machine learning, and big data will help the growers of the future to make decisions and optimize the crop protection management of their vineyards to meet their established objectives, providing useful information both in the vineyard and fruit orchards (Mahlein et al., 2019; Gutiérrez et al., 2018). The combination of data from different sources of soil-plant-environment could be important to obtain information and make forecasts to optimize crop protection management, leading to sustainable agriculture.

5.4 Conclusions

Many new technologies have been developed and are currently being investigated for fruit orchards and vineyards for managing pests and diseases. New technologies can be applied to crop protection. New reliable, objective, rapid, and field-deployable crop disease and pest detection methods are needed. Artificial intelligence and new non-invasive technologies will help growers in the future to make decisions and optimize fruit orchards and vineyard management in line with set targets. Combining data on both the plant and environmental factors will be important in obtaining useful information and making predictions that can optimize pest and disease management and hence sustainable vineyards and tree fruit orchards. Even though many new technologies have been developed and applied to crop production, more effort will still be needed, especially for disease and pest management, with more interest and support from growers, industries, and state and federal agencies.

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Chapter 6
Advanced Technologies for Crop-Load Management

Manoj Karkee, Yaqoob Majeed, and Qin Zhang

Abstract This chapter will discuss the opportunities and challenges of robotic solutions for tree fruit production with modern planar tree canopy management, including the importance of modern tree canopy system, robot-canopy interaction, robotic system control, in-field sensing for object detection, and three-dimensional (3D) reconstruction, and a case study on the robotic branch pruning for apples with modern tree canopies. In the end, the conclusion and future directions were investigated.

6.1 Introduction

Crop-load management is one of the most important tree fruit crop production operations. Fruit trees generally bloom more flowers and set more fruit than they could support to grow the desired yield of high-quality fruit (e.g., size, color, and internal characteristics such as sugar content and acidity). Precise crop-load management practices aim at optimizing the yield and these quality parameters by adequately reducing the number of fruit set and grown in a given tree. Overall crop-load management of fruit crops is commonly achieved through a strategic combination of training, pruning, thinning (flower and fruit), and/or pollination to control the number of fruit grown in individual trees.

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6.1.1 Tree Training

Tree training is an operation that creates desired tree canopy architectures with different heights, shapes, and structures. In modern orchards, trees are generally trained to a trellis system (consisting of trellis posts and trellis wires) right after planting so that the trunk of the trees grows to a specific shape and direction. Once the trunks are securely trained to a specific shape and grow to a certain height, newly growing branches are also trained to form canopy shapes. Modern training systems are designed to create narrow canopies in vertical or angled structures, often called SNAP (simple, narrow, accessible, productive) orchards. Figure 6.1 shows an upright fruiting off-shoot (UFO) cherry architecture where the main trunks are trained to create a permanent horizontal structure and branches are grown and trained vertically above the base.

Two other commonly used training systems in modern orchards are presented in Fig. 6.2. Figure 6.2b depicts a formally trained apple orchard in a V-trellis system where tree trunks are trained upright at a certain angle and branches are trained horizontally along the trellis wires creating canopies with layers of fruiting zones.

These training systems are designed to improve air movement and light distribution and make fruits and branches more visible. The trees are friendlier to both manual and automated field operations. Consequently, modern, narrow canopy architectures help maximize both the yield and quality of fruit crops compared to conventional three-dimensional trees (Fig. 6.3). More details on tree pruning concepts and their roles in fruit crop production were presented in Chap. 2.

6.1.2 Tree Pruning

Tree pruning is an operation to help grow trees into a desired shape and size, which is essential to improve the penetration of both sunlight and spray materials to all canopy parts, supporting more effective orchard operations. Pruning is also used to

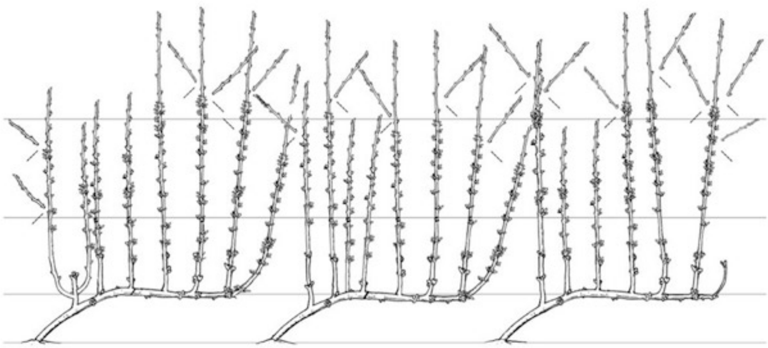

Fig. 6.1 Illustration of UFO cherry tree training and pruning. (Diagram courtesy of Dr. Mathew Whiting, Washington State University)

Fig. 6.2 A well-pruned vertical trellis (**a**) and V-trellis (**b**) system commercial apple orchard in the state of Washington which produces a high yield of good size and high-quality apples. (Photo by Qin Zhang)

Fig. 6.3 Traditional low-density sweet cherry orchard. (Pictures from Zhang 2017)

remove old and diseased branches. Otherwise, unproductive branches initiate new growth and improve flower bud development (Durner, 2013) so that the overall tree health and productivity remain at an optimal level. In modern orchards, pruning operation can also regulate fruit-bearing sites so that light interception to fruit can be enhanced and uniformity of fruit distribution over the canopy surfaces is improved, which leads to improved yield and quality of fruit crops. Pruning is typically done annually by selectively cutting and removing parts/branches of trees following certain guidelines developed by horticultural research and farmers' long experience. Therefore, achieving desired pruning results requires experienced workers with adequate knowledge and skills in pruning strategies. Figure 6.4 shows a well-pruned apple orchard in the state of Washington.

Fruit tree pruning could be conducted in the winter (dormant season) and the summer. Dormant pruning is performed from late fall to winter when the trees are not actively growing. This is the annual pruning process's major part of maintaining

Fig. 6.4 A well-pruned commercial apple orchard in the state of Washington which produces a high yield of good size and high-quality apples. (Photo by Qin Zhang)

Fig. 6.5 A graphical illustration of a few commonly used hand pruning tool samples – (**a**) a hand pruner, (**b**) a long-handled lopping shear, and (**c**) a pruning saw – and powered pruning tool samples: (**d**) an electric-powered pruner, (**e**) a pneumatic-powered pruner, and (**f**) a hydraulic-powered pruner

the desired canopy shape and size. Some farming operations also perform summer pruning, focusing primarily on removing excessively growing shoots or branches to optimize fruit exposure to sunlight. Fruit tree pruning is mainly done manually by skilled field workers using hand tools, such as hand pruners, long-handled lopping shears, or pruning saws (Fig. 6.5a–c). As hand pruning is highly labor-intensive (the second-highest labor-intensive job after harvesting) and accounts for ~20% of the total production cost (He & Schupp, 2018), some power-pruning tools, such as electric-, pneumatic-, or even hydraulic-power pruners (Fig. 6.5d–f), are increasingly being used for reducing the force required to cut branches and thus to reduce the workers' fatigue and improve their productivity. Personal communication of authors with growers in Washington has suggested that it could achieve about a 50% labor-saving in orchard pruning by simply switching from using hand tools to the use of power-pruning tools.

6.1.3 Blossom and Fruit Thinning

In general, even after strategic pruning, most fruit trees bloom many more flowers than needed for an optimal fruit set. If all flowers are left for pollination, it could result in too many fruits being set, leading to harvested fruits with small/suboptimal size and often with poor quality. Experts estimated that for some varieties of tree fruit crops such as apples if just 5% of all those spring flowers set fruit, it could be enough to provide the desired crop yield. Thus, many fruit growers have adopted flower and/or fruit thinning as a good farming practice to remove either a portion of the blooms or young fruits (or both) on the trees for growing fruit with good size and high quality.

Blossom thinning can be performed using either chemical approaches to reduce the number of flowers capable of setting fruits or physical means to remove a portion of flowers from the trees during and shortly after the bloom period. An additional green fruit thinning could also be performed later in the season (anywhere from a couple of weeks to a few months after fruit set) to remove excess and poor-quality fruit and/or those growing in suboptimal canopy areas and growing too close together, to ensure good size and quality of fruits at harvest. Chemical thinning is a less labor- and skill-intensive operation than pruning, but physical/manual thinning could be very tedious and time-consuming, which thus could be as or even more expensive field operation compared to pruning.

Chemical thinning is mechanically performed by spraying some plant growth-regulating chemicals on the trees shortly after bloom; this is a highly productive operation. However, despite many years of study and practice, chemical thinning remains unpredictable in efficacy. Its results could vary significantly from orchard to orchard or year to year due to a wide variation of field and/or weather conditions. Thus, it is still more an empirical method requiring growers to weigh many factors in planning a thinning operation to obtain a desirable response from chemical thinning.

Physical blossom thinning can be done mechanically using machines or manually using tools or even hands (from left to right in Fig. 6.6). In general, hand thinning is the most labor-intensive and laborious approach with very high labor costs, even though it could achieve the most precise control over the thinning efficacy. Using some kinds of hand tools could help solve the low productivity and high labor cost challenge, with a price of less controllability in thinning precision. Mechanical thinning is highly productive but has the least controllability in thinning precision.

Fig. 6.6 Examples of blossom thinning using a machine (left), a hand tool (middle), or hands (right) in commercial cherry orchards in the state of Washington. (Photos by Qin Zhang)

6.1.4 Crop Pollination

As fruits can be set only after the flowers are pollinated and fertilized, pollination plays a critical role in transferring pollen from male to female parts of flowers to set the fruit. Thus, crop pollination and its efficient control become one of the most important field operations for achieving desired crop load in fruit trees. In general, there are two types of pollination approaches in fruit trees: self-fruiting/self-pollinating crops and externally pollinating crops (cross-pollination). Pollination in self-pollinating crops occurs by transferring pollen from the anther to the stigma in the same flower and between different flowers in the same tree or between flowers in different trees of the same cultivar. Because pollination in self-pollinating crops can occur within the same flower, it is difficult to realize crop-load management by controlling the amount of pollination.

There are other fruit crop cultivars where self-pollination (setting fruit using the pollen from the same flower or tree) is not possible. In such crops, cross-pollination between different fruit cultivars is required for the fruit set. Cross-pollination in commercial orchards is achieved by planting pollinating trees at a certain density so that pollens from the pollinating trees are transferred to the flowers in the crop trees. Transferring of pollens from pollinator trees to crop trees is achieved by some pollinating agents, such as bees, insects, birds, water, and/or wind. Such a pollination process requiring external agents for pollen transfer offers a possibility of managing crop load using a controlled amount of pollination.

Conventionally, tree fruit growers worldwide have relied on natural means, such as insect pollinators or wind, to complete the pollination process. Due to some ecological and disease control reasons, such as a persistent decline in bee populations (e.g., colony collapse disorder), insects' sensitivity to environmental conditions, and the potential for viral disease distribution, tree fruit growers are looking for alternatives to the natural pollination process. More discussion on mechanical and robotic pollination is presented in Sect. 6.4.

6.2 Advancement in Training and Pruning Technologies

6.2.1 Introduction

Using manual labor, fruit trees are trained and pruned to the desired shape and size. These are highly labor-intensive operations requiring a large semi-skilled labor force on a seasonable basis. With decreasing availability and increasing labor costs, it has been increasingly challenging for tree fruit growers to complete these annual operations to the desired level. To improve the sustainability of the fruit crop industry, it is essential to develop automated or robotic solutions for these labor-intensive field operations (Hertz & Zahniser, 2013).

As discussed before, fruit trees are pruned to improve the fruit quality and yield by removing unproductive branches and branches in undesirable locations. Pruning helps create the desired size and shape of the trees and set the desired structure for optimal crop load. Manual pruning involves the selective removal of branches by skilled labor. Mechanically or with automated machines, pruning can be carried out in non-selective (hedging/mass removal) or selective fashion. Moore (1958), Gautz et al. (2002), and Forshey (2014) worked on mass pruning systems in which a cutting tool was run over tree canopies to keep a predetermined distance from the center of tree canopies.

Similarly, Morris (2007) developed a mechanical solution for the non-selective removal of shoots at a certain height above the cordons (permanent horizontal vine) in vineyards. These machines achieved a good performance in cutting branches in mass at a certain canopy depth and hedging at a certain height (Forshey, 2018). However, manual cleaning after a mass pruning operation is essential to achieve the desired pruning outcomes in terms of uniform distribution of fruiting sites, renewal of unproductive branches, and better exposure of fruit to sunlight.

While these machines are easy to operate, this process does not allow for selective pruning or renewal of tree branches, which is essential to achieve canopy shapes that maximize yields of premium quality fruit. Therefore, a robotic solution would be essential to selectively remove tree branches using a manipulator and end-effector system to achieve the best pruning results. The latest research and development in selective pruning of fruit trees and grapevines will be discussed in the following subsection.

6.2.2 Machine Vision for Selective/Robotic Pruning

Robotic pruning of trees consists of four main steps: (i) perceiving the visual information and creating the 3D structure of target fruit trees using a vision system; (ii) determining the branches to be pruned (pruning decision) using various pruning strategies and 3D structure of the trees; (iii) path planning and navigation of the manipulator to target branches; and (iv) selectively removing branches using an end-effector. Accurate estimation of 3D tree structures and precise execution of all these steps of the robotic pruning process are vital to achieving the desired pruning results in an orchard environment.

In the first step, machine vision techniques are applied to obtain images, remove background, detect various canopy parts (e.g., trunk and branches), and reconstruct the tree structure. In this process, various object features, including color, shape, texture, and location (e.g., distance to a branch from the sensor), are extracted explicitly or implicitly (e.g., in a deep learning model) and used to accomplish object detection and classification as needed. At this stage, errors and/or inaccuracies affect all downstream operations and, therefore, the performance of the overall robotic pruning system.

As a sensing/vision system is the fundamental component of a robotic pruning system, many researchers worldwide focus on developing an accurate and robust vision system for robotic pruning. Naugle et al. (1989) investigated the use of machine vision to guide an automated pruning device. RGB cameras were used by McFarlane et al. (1997) and Gao and Lu (2006) to capture images of grapevine canopies in vineyards. Then, simple image processing techniques (i.e., color thresholding and Hough transform) were applied to segment the grapevines in the images.

Similarly, two RGB cameras mounted on a robotic manipulator were used to acquire images of dormant apple trees by Tabb and Medeiros (2017). They used a silhouette-based algorithm for extracting the skeleton of apple trees. They then estimated different geometric and topological characteristics of trees, including diameter, length, and angle of branches, that could help determine pruning points for the robotic pruning systems. You et al. (2021) produced labeled skeleton of upright fruiting off-shoot (UFO) cherry trees in color images using the topological and geometric priors associated with these labels. A median accuracy of 70% regarding a human-evaluated gold standard was achieved by creating a skeleton of cherry trees using this algorithm.

Color and 3D or just 3D sensing systems have also been widely investigated to reconstruct fruit trees and estimate desired geometric color and topological parameters desired to make pruning decisions. Livny et al. (2010) proposed a branch structure graph (BSG) to create and represent skeletons of trees in the dormant season. Tabb (2013) developed 3D models of apple trees using the principle of shape from Silhouette. Chuang et al. (2000) used shape information called potential field to extract the skeleton of 3D objects. Palagyi et al. (2006) proposed an end-point rechecking method to avoid spurious side branches generating the skeletons. These algorithms have shown good accuracy in indoor applications. Elfiky et al. (2015) proposed a new 3D reconstruction method for apple trees trained in a tall spindle architecture. They used the Microsoft Kinect 2 sensor, which showed the potential for a low-cost sensor for orchard machine vision applications. Akbar et al. (2016) and Chattopadhyay et al. (2016) developed and evaluated a method to model tree trunks and branches using semicircles in a 3D space represented by a single depth image. A stereo vision camera was used to acquire 3D point cloud data of sweet cherry trees by You et al. (2021) for the robotic pruning. Then, a

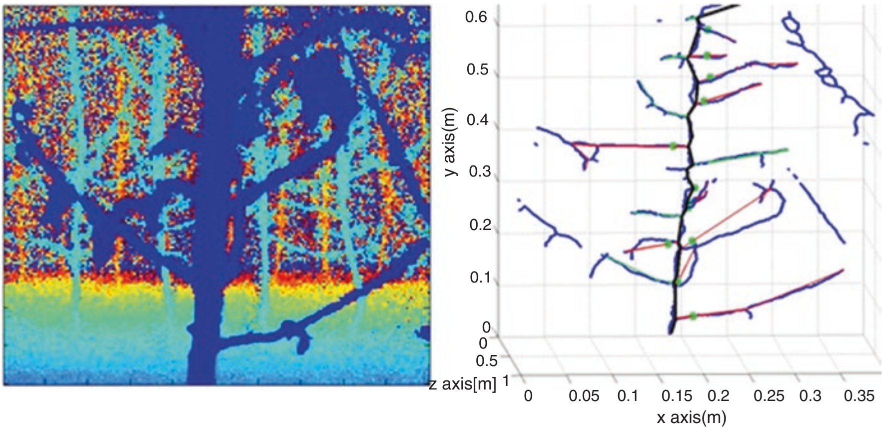

Fig. 6.7 Apple tree captured by a 3D camera (left) and identified pruning points in the tree skeleton (right)

population-based search algorithm was applied to skeletonize the cherry tree, and a CNN (convolutional neural network) was used to validate the correct edges of the skeleton.

In addition to consumer 3D cameras, a laser scanner was employed by Medeiros et al. (2017) from various perspectives to collect 3D information on dormant apple trees. A split-and-merge algorithm was applied to separate the trunk, branch, and joint segments. Once the trunk and branches were delineated, diameters of the trunk and branches were estimated, which is considered an important parameter to determine the target branches for pruning. The technique was tested in tall spindle apples and other relatively older tree architectures. A 3D camera (mounted on a pan-and-tilt system) based on the time-of-flight of light principle was used by Karkee et al. (2014) to capture image frames of apple trees for dormant robotic pruning. The skeletons of apple trees were reconstructed by adopting the medial-axis-thinning algorithm. Skeletonized trees were used to identify pruning branches following two simple rules, i.e., maintaining a specific distance between branches and maintaining a specific branch length (Fig. 6.7).

In recent years, low-cost, consumer RGB-D sensors have also been investigated widely to create the 3D structure of fruit trees. Wang and Zhang (2013) used Kinect sensors mounted orthogonally to the canopies for collecting 3D information and used a simple transformation matrix to reconstruct the skeleton of cherry trees from 3D point cloud data. Elfiky et al. (2015) employed a Kinect sensor to acquire a 3D point cloud of dormant apple trees from the front and backside. Then, they used a skeleton-based geometric-feature algorithm for the 3D reconstruction of the trees. The study also proposed a circle-based layer-aware algorithm to locate the pruning points on target branches of apple trees.

Similarly, Akbar et al. (2016) acquired the depth images of dormant apple trees using a Kinect sensor. A 3D reconstruction of the apple tree was carried out using the semicircle fitting scheme. The study then proposed empirical models to estimate the diameter of primary branches, which could help identify branches for robotic pruning.

In summary, the 3D reconstruction approaches discussed above primarily used the following steps leading to a tree skeleton that can be used for implementing pruning strategies: (i) 3D scan the tree using LiDAR (3D point cloud) or images (3D point cloud reconstructed from stereo images, structure-from-motion or optical flow); (ii) separate the 3D points into tree branches, ground, and leaves based on imaging properties and/or user intervention; (iii) reconstruct the main tree branches using a mix of a priori knowledge (branches/trunk that are essentially cylinders that get smaller and branching points) and user input (marking branching points or sketching branches); and (iv) "fill in" missing parts of the scan (particularly smaller branches and missing geometry) using the estimated density of the leaves and expected shape of the branches.

Similar to many other areas of image processing, deep learning-based techniques have also been introduced in processing tree canopy images to detect objects and classify image regions. For example, semantic segmentation and deep-learning based techniques, in general, have shown increased accuracy and robustness in analyzing orchard images and have helped reduce the impact of uncertain and variable lighting and environmental conditions.

6.2.3 Pruning Strategies and Rules

After image segmentation and 3D reconstruction/skeletonization of fruit trees, the next important step is to use experts' (e.g., horticulturists and experienced growers) knowledge and their pruning strategies to create rules to algorithmically identify and locate target branches for pruning. Some of the major goals of pruning include distributing fruiting sites as uniformly as possible, renewing fruiting branches, and removing unproductive branches.

In general, growers prune tree branches in the dormant season using "renewal cuts," "pruning cuts," and "trimming" cuts (Table 6.1). Renewal cuts are for those branches that are too big or unproductive, which are cut at the base (e.g., right next

Table 6.1 Sample pruning/hedging rules

R1	If a neighbor branch is closer than X, then it is a "close" branch
R2	If a branch is longer than Y, then it is a "long" branch
R3	If a branch has long section w/o buds, then it is a "blind" branch
R4	If a branch is dead, then it is a "non-productive" branch
R5	If a branch diameter is larger than Z, then it is a "large" branch
R6	If a branch is "close," then it is a "pruning" branch
R7	If a branch is "long," and *not* "close," then it is a "pruning" branch
R8	If a branch is "large," and *not* "close," then it is a "renewal" branch
R9	If a branch is "long," *not* "large," and *not* "close," then it is a "hedging" branch

to the trunk). Long branches are cut back to a certain length for trimming cuts based on the tree canopy design. Pruning cuts are used to keep variable branch lengths to optimize fruiting sites or uniformity and improve fruit quality. Though the goals are common, almost every grower has a strategy to identify pruning branches in a tree, which often involves substantial subjective judgment. A set of relatively complex rules will be necessary to represent such subjectivity and achieve desired pruning outcomes. To convert such human expert knowledge precisely and consistently to rules that can be implemented by the machine, a "soft-words" computation model such as the one proposed by Zadeh (1999) can be used. For example, basic rules (e.g., R1 in Table 6.1) will be used to deduce more complex rules (e.g., R9) necessary to achieve various pruning goals.

Manual pruning is performed by skilled laborers trained to follow specific strategies provided by farmers or managers. The desired number of fruiting sites can be maintained in each tree. However, as mentioned before, pruning guidelines vary substantially between tree architectures, fruit cultivars, and even individual growers and operations. Therefore, any developed solution for robotic pruning must consider canopy architectures and crop cultivars. To some extent, current manual pruning practices are also based on individual experiences and art in addition to research-driven strategies. Therefore, they lead to substantial variability and inconsistency between different workers pruning the same tree and the same worker pruning different trees. Putting these human judgment-based strategies and practices into objective rules for the robotic system to implement (similar to Table 6.1) is challenging. There are certain quantitative guidelines that farmers would like to follow, including measurement of branch diameter and pruning side branches such that the right amount of fruiting sites could be left for each branch based on its fruit-bearing capacity. However, in practice, such quantitative guidelines are rarely practiced, reducing workers' productivity substantially. Even in such a situation where it is easier and faster for a vision system to estimate branch diameters, it is challenging to implement such a strategy by machines because we lack sensing systems that can accurately and reliably estimate the number of fruiting sites (vegetative buds and flowering buds look similar to even untrained human eyes) and identify diseased branches during the dormant season.

Only a few studies have placed some effort in creating simplified objective rules that machines can implement for the robotic pruning of fruit trees. Further studies on developing effective and reliable sensing systems for flower bud detection and diseased and dead branch identification, as well as developing objective pruning strategies for consistent and robust robotic pruning, would be essential.

As discussed earlier, Karkee et al. (2014) conducted interviews with expert horticulturists to understand their decision-making process for pruning apple trees in large commercial orchards in Washington State. This study found that there are four basic rules for pruning in SNAP or fruiting wall architectures; these are to remove (i) diseased branches, (ii) long branches, (iii) large branches, and (iv) closely spaced branches. Although these rules appear simple, this study also revealed various challenges, including (1) difficulty detecting the required targets, such as dead branches, and (2) identifying pruning points and steps in complicated canopies that often require judgment and potentially complex pruning rules. Therefore, in their study, they used two simple rules that machines could implement: (i) remove long branches (when length > user-defined threshold) and (ii) remove one of the two closely spaced branches (when spacing < user-defined threshold). Based on the analysis of 20 reconstructed tree models, the algorithm achieved 77% accuracy in identifying tree branches. On average, the algorithm suggested the removal of 19.5% of branches, whereas, in the same situation, human workers suggested 22% removal.

Similarly, Dr. James Schupp (Penn State University) worked with engineers to identify rules for automated pruning of tall spindle apple trees (Lehnert et al., 2015). He proposed eight pruning rules for fruiting wall apple orchards, including "Maintain a narrow cone shape by thinning outshoots that are more than 30 inches long in the top," "Remove any secondary limb when its diameter becomes more than half the diameter of the leader," and "Remove all damaged or diseased limbs." Four of these rules were the same as Karkee et al. (2014) proposed. On the other hand, Liu et al. (2019) attempted to develop the back propagation (BP)-based neural model to make pruning decisions for the robotic pruning of apple trees. Similarly, Saxton et al. (2014) and Corbett-Davies et al. (2012) presented preliminary work on developing an expert system for understanding the pruning process from human experts and used the system to establish the best practice for robotic pruning in vineyards.

6.2.4 Integrated Pruning Systems

The vision and pruning decision systems need to be integrated with a robotic manipulator and an appropriate end-effector (hand) to perform robotic pruning in fruit trees. Even though modern SNAP fruit canopies offer simpler tree structures than traditional fruit trees, fruit trees still include a lot of branches growing randomly in all possible directions and often crossing each other in different parts of the canopies. In addition, tree canopies include trunks, trellis posts, and trellis wires. Such a canopy environment presents many obstacles to robotic manipulators and end-effectors. As the system approaches target branches for selective pruning, obstacles can cause collisions with the robot, which severely affects the performance of the robotic pruning system and can cause damage to the manipulator and end-effector. Therefore, there is a critical need for efficient and effective path planning and navigation to find the optimized path to reach the target branches avoiding collision with branches and/or other obstacles.

As described earlier, most of the work related to robotic pruning was carried out by focusing on its components, particularly the vision system. Only a few studiesfocused on the overall system integration and path planning in fruit crops. However, there are a few more studies conducted in grapevines as well. You et al. (2020) and ongoing work at author Karkee's lab have developed an integrated robotic system using a UR5 (a six-DoF manipulator by Universal Robots, Odense, Denmark) manipulator and a scissor cutter-type end-effector (Fig. 6.8). The system uses

Fig. 6.8 Integrated robotic system for selective pruning of apple and cherry trees developed by researchers at Washington State University and Oregon State University. (Photo by Manoj Karkee)

consumer RGB-D cameras (e.g., Zed 2, Stereolabs Inc.) to collect color and depth information and create the 3D structure of trees. They presented an algorithmic framework for this robot's path planning. The system first moves the end-effector to the approach pose and then follows the linear approach to reach the targeted position. Motion planning was implemented using Fast-Reliable-and-Efficient-Database-Search-Motion-Planner (FREDS-MP) framework, which computes the optimistic trajectories (Sukkar, 2017). A robotic system, including the path planning method, has been evaluated in the lab environment, and further development and field evaluations are continuing.

Zahid et al. (2020) also used the UR5 manipulator for the collision-free path planning to prune apple trees. They employed the Rapidly-exploring-Random-Tree (RRT) algorithm to find the collision-free path. A nonlinear optimization technique was used to find the optimized path among the various alternatives to reach the target position. Magalhães et al. (2019) benchmarked different path planning algorithms from Open Motion Planning Library (OMPL) using a 6-DoF manipulator for grapevine pruning.

Lee et al. (1994) reported work in the electro-hydraulic control of a vine pruning robot. Kondo et al. (1993, 1994) developed a manipulator and vision system for a multipurpose vineyard robot. Similarly, Botterill et al. (2017) developed a complete pruning robot for pruning grapevine canopies and tested it in a commercial vineyard. This system consists of an enclosed mobile platform (Fig. 6.9), which can completely cover the grapevine canopies (to block the sunlight and background canopies) and houses high-intensity LEDs (light-emitting diodes), a trinocular stereo camera system, a robotic arm (6-DoF UR5) mounted with a drill bit (to prune canes), a generator, and a desktop PC. A trinocular stereo camera system was used to capture the images of grapevine canopies under constant lighting conditions

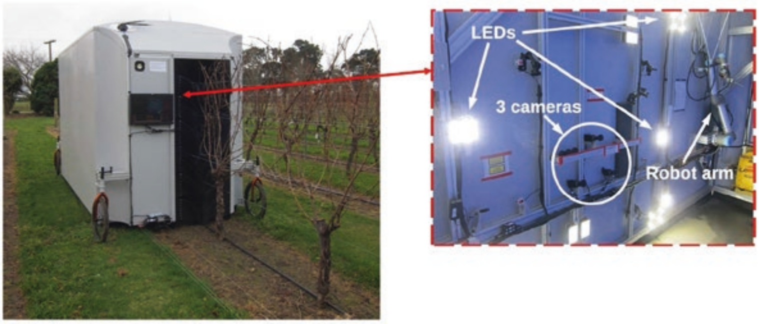

Fig. 6.9 A mobile platform for pruning grapevines that houses the high-intensity LEDs (light-emitting diodes), a trinocular stereo camera system, a robotic arm mounted with a drill bit (to prune canes), a generator, and a desktop PC. (Pictures from Botterill et al. 2017)

using LEDs. Then, a triangular-feature-matching algorithm was used for the 3D reconstruction of grapevine canopies. An AI-based algorithm was then developed to make pruning decisions. An RRT-based path planner was used for path planning and navigation with collision-free trajectories. They state that the main bottleneck in their work was the time required for online planning and motion execution. This robot system can estimate the trajectories at the rate of 0.25 m s^{-1} and takes about 1.5 s for each vine to calculate the collision-free trajectory for the manipulator. The robot took ~2 min to prune each grapevine canopy.

These studies showed that end-effector design selections strongly influence pruning performance. For example, reducing the bounding volume of the design increases the likelihood of finding a collision-free goal configuration and path. For pruning grapevine canes, Botterill et al. (2017) developed a manipulation method whereby the robot swept through the pruning zone using a rotating end mill cutter. One issue they reported was the tendency for the cutter to push the cane away from the pruning zone, leading to pruning failures. Zahid et al. (2019) developed a prototype end-effector that used scissors/shears to cut small-diameter apple tree branches.

A similar robotic pruner was developed by Katyara et al. (2020) and was tested in laboratory conditions. This robotic system consisted of a 7-DoF manipulator (Franka Emika, München, Germany), two Intel RealSense cameras (D435i, Santa Clara, California, USA), and a shear pruner attached at the end-effector of the manipulator. Intel RealSense camera was used to capture the images of grapevines. Then a Faster R-CNN (faster region-based convolutional neural network) (Ren et al., 2015)-based model was used to detect spurs/shoots. Once the spurs were detected, a statistical-pattern-recognition algorithm was used to determine the pruning points. This pruning robot dealt with only a single cordon (one side) of grapevine canopy at a time and took ~49 s to prune 5 shoots compared to ~8.4 shoots on average (due to focus on the complete vine) per vine in Botterill et al. (2017) taking ~2 min.

Although there have been several studies on developing robotic pruning systems for tree fruit crops and vineyards around the world, there has been no commercial success so far in adopting those technologies. Lack of commercial success is primarily caused by (i) limitation of perception techniques in representing the 3D structure of trees in the presence of variable and uncertain outdoor environments and self-occlusion of branches accurately; (ii) challenges in representing the pruning process with objective pruning rules that a machine can implement; and (iii) high cost and slow speed of the overall robotic system. Recent studies, such as the projects currently carried out by WSU and Oregon State University team (You et al., 2020, 2021), focus on some of these challenges, including learning from human knowledge and creating objective pruning rules. It is anticipated that future work is necessary and will be focused on developing simpler and faster 3D reconstruction methods for fruit trees in modern fruiting wall architectures such as formal apples and upright fruiting offshoot (UFO) cherries (Fig. 6.1), which are the most suitable architectures for robotic operations like pruning. In addition, new sensing studies on floral bud detection and detection of diseased and dead branches would be essential in the future. Further studies in developing objective pruning strategies for consistent and robust robotic pruning would also be critical. More discussion on general challenges and future opportunities will be discussed in Sect. 6.5.

6.3 Precision Thinning

6.3.1 Introduction

As discussed in Sect. 6.1, the production of high-value trees and fruit crops such as apples and cherries requires a large, semi-skilled workforce for short, intensive periods during the year. One of the most labor-intensive orchard activities is bloom and green fruit thinning. Bloom thinning involves selectively removing closely spaced flower clusters and/or several individual flowers from within a cluster. Only a desired number of flowers are left for pollination (typically only one). Green fruit or fruitlet thinning is similar to removing closely spaced and clustered fruit so that only a desired number of fruits are left to grow. Flower and green fruit thinning are two critical perennial operations necessary to balance fruit quantity and quality to achieve the target yield and returns for premium fruit.

Growers can deploy chemical bloom thinners or tractor-driven mechanical string thinners as an alternative to manual flower thinning. Nearly a century of research has yielded chemical thinning programs that are marginally effective and inconsistent. Washington's tree fruit research commission has investigated chemical bloom thinning programs for decades and found that the best program was effectively less than half the time (T. Schmidt, personal communication, 2021). In addition, there are handheld and tractor-mounted mechanical flower thinning machines available commercially.

A handheld mechanical device was also tested on the cherry trees for blossom thinning based on the same string thinner concept (Wang et al., 2013). Rosa et al. (2008) presented an electro-mechanical device that shakes the limbs for the fruit thinning of different fruit trees, i.e., nectarine, peach, prune, etc. Though these mechanical solutions helped reduce labor usage, they still lack precision because of their non-selective nature and high variability in their efficiencies. However, these "mass" thinning systems do not allow for selective removal of flowers/flower clusters and lack desired precision. There is no practical alternative currently available to manual thinning when it comes to green fruit thinning. In recent years, recognizing these challenges, researchers worldwide have been working on developing automated flower and green fruit thinning solutions.

6.3.2 Flower and Green Fruit (Fruitlet) Thinning

An automated/robotic flower or green fruit thinning system consists of a vision system to detect and precisely locate flowers and flower clusters in tree canopies, a manipulator to approach the target locations, and an end-effector to effectively remove the desired proportion of flowers or green fruit from target locations. Contrary to the dormant pruning of fruit trees discussed in Sect. 6.2, thinning is carried out in the growing season when canopies include shoots, leaves, flowers, and/or fruits in addition to trunks, branches, and trellis wires (Fig. 6.10). Such complex canopies pose greater challenges for a robotic/automated system to accurately detect and position the target objects (because of a heavy occlusion of target objects by other canopy parts) and access them for precision thinning. It is also essential that flower detection models have a high computational speed for real-time, in-field operation.

Fig. 6.10 Trellised canopies

Researchers have developed conventional and deep learning-based models to detect flower clusters in apple and cherry orchards (e.g., Aggelopoulou et al., 2011; Dias et al., 2018a, b; Farjon et al., 2020) that can provide a foundation for flower thinning as well as robotic pollination (Sect. 6.4). These efforts mostly relied on color (RGB) images captured from close distances (0.5–1.5 m) with varying pixel resolutions. Aggelopoulou et al. (2011) used the RGB cameras to collect the images and map the flower distribution of blossomed apple trees to adjust chemical thinning rates for precision application. Similarly, Hočevar et al. (2014) also used an RGB camera to capture the images of apple trees during bloom to estimate the number of flowers, which could assist in precision blossom thinning. Dias et al. (2018a) used the commercially available RGB camera to collect the images of apple trees for the blossom thinning task. Then, the CNN (convolutional neural network) and SVM (support vector machine) algorithms were used to detect the flowers from RGB images. In another study by Dias et al. (2018b), semantic segmentation was carried out for detecting flowers in apple, peach, and pear trees using a residual CNN-based technique. Tian et al. (2020) proposed an improvement over the Mask R-CNN model for segmenting out apple flowers using RGB images of apple trees collected during different bloom stages. Once flowers are detected, their 3D location would be essential for robotic thinning and pollination (Sect. 6.4).

Various types of 3D imaging techniques, such as laser scanners, stereo cameras, time-of-flight 3D cameras, and recently developed consumer RGB-D cameras (e.g., Zed 2, Stereolabs Inc.), can improve the detection and localization of flowers. A 3D imaging system consisting of a video camera and plane laser scanner was used by Emery et al. (2010) to detect and locate blossoms in peach trees for precision blossom thinning. Nielsen et al. (2011) used a stereo-vision camera system to map blossoms in peach trees for precision blossom thinning. Similarly, Underwood et al. (2016) used a color camera and 2D LiDAR sensor mounted on a ground robot to scan almond trees during different fruit-bearing stages (peak bloom, fruit set, and just before harvest) to estimate yield, which could assist in precision blossom thinning. Bhattarai et al. (2020) collected RGB-D information in apple orchards using a Kinect sensor to develop a machine vision system for robotic blossom thinning (Fig. 6.11). Segmentation of apple flower clusters was carried out using a Mask R-CNN-based model.

The earliest indication of potential crop load in a given tree would be the number of flowering buds. Good estimation and localization of buds would help make desired pruning and flower thinning decisions. Only highly trained human eyes can differentiate if a given bud will be a vegetative bud or a flowering bud in the crops like apples and cherries. The authors' experience in the field has shown that it is challenging to develop a machine vision model that can differentiate vegetative and floral buds using only color and shape features. However, there have been some efforts to develop spectral sensors that go beyond the color and shape information so that a reliable, automated floral bud counting system could be developed. For example, Wouters et al. (2015) mounted a multispectral sensor on the ground-based mobile platform to detect pear tree floral buds.

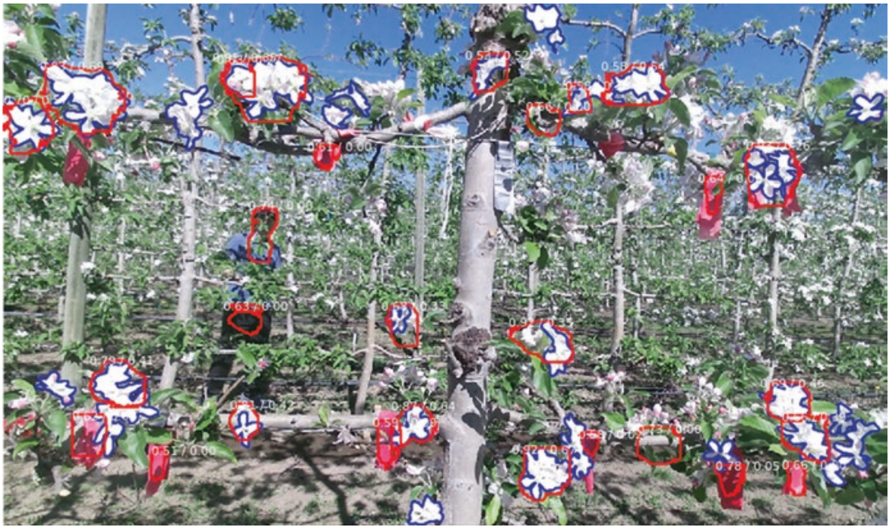

Fig. 6.11 Blossom detection with deep learning; blue and red polygons indicate ground-truth and detection results, respectively

6.3.3 Integrated Thinning Systems

In addition to machine vision systems, there have been efforts to develop integrated automated or robotic systems for flower thinning. For example, Aasted et al. (2011) mounted a LiDAR scanner on a tractor and string thinner, which sensed the flower density in apple tree canopies and automatically controlled the position and orientation of thinning heads for precision blossom thinning. Lyons et al. (2015) developed an automated precision blossom thinning system for peach trees. This system consisted of a six-DoF robotic arm and rotating brushes mounted at the robot's end. A stereo-vision-based system developed by Nielsen et al. (2011) was used to detect thinning targets. A heuristic algorithm was used to mimic the ways growers make thinning decisions. This precision blossom thinner achieved a ± 10.33% margin of error to place the thinning end-effector at the target position.

Similarly, Ou Yang (2012) developed an integrated robotic platform targeting the robotic blossom thinning of peach and tested it on the model tree. This system consists of a custom-build six-DoF manipulator and clamp-type end-effector. An inverse kinematic-based task planning algorithm was used to reach the targeted locations. This system takes around 7.7 s to find the path toward the target.

Currently, green fruit thinning is largely manual, and there have been only a limited number of efforts in developing machine vision and integrated systems for robotic thinning. Xiong et al. (2020) completed one tangentially relevant study using an unmanned aerial system (UAS) to collect RGB images of mango trees. Then, the YOLOv2-based deep learning model was used to detect green mangoes to estimate yield. Similarly, as discussed before, Underwood et al. (2016) used a ground robot to scan almond trees during the green fruit stage to estimate crop yield. These studies could provide some basis for developing robotic fruit thinning systems in the future.

As with robotic pruning, robotic thinning has not been commercially adopted yet. Robotic thinning faces the same challenges, such as lack of desired speed and high cost. In addition, a few specific factors make robotic thinning uniquely challenging to reach its full potential in in-field operation. First, there has been a wide range of studies on detecting flowers in fruit trees, as discussed before. However, these studies have only successfully segmented flower regions. Detecting individual flowers within a given cluster and estimating their orientation remain a great challenge for precision robotic thinning and robotic pollination (Zhang, 2017). Second, the robotic thinning of individual flowers of fruit crops such as apples and cherries is challenged by their small size, their growth in tight clusters, and high level of self-occlusion, making it almost impossible to approach and selectively remove individual flowers. Under these constraints, current efforts in robotic thinning have been to delineate individual clusters of flowers and use an end-effector that can remove a proportion of flowers within the cluster without regard to type, location, and developmental stage of flowers. In these efforts, multiple off-the-shelf end-effectors operated via different actuation mechanisms were investigated and evaluated for their performance in blossom thinning, including pneumatic hose, waterjet, and electrically actuated wire brush system. Additionally, the effectiveness of commercially available handheld blossom thinner, Bloom Buster/Bandit, from Automated Ag was tested. The miniature design of a similar concept to Bloom Bandit showed better efficiency for precision thinning (Fig. 6.12).

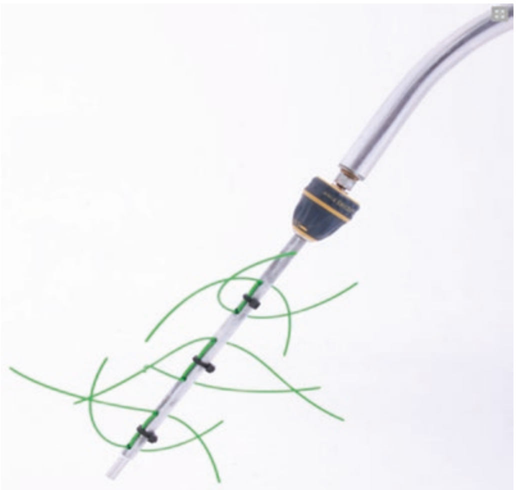

Fig. 6.12 Miniature design of a Bloom Bandit for precision thinning. (Picture from https://www.automatedag.com/bloom-buster-gallery)

In the future, it is important to put more effort into developing decision support tools for the integrated systems to achieve the desired level of flower and green fruit thinning. Moreover, continual improvement of the manipulation and end-effector technologies for precision thinning would be essential to improve the accuracy and speed while reducing the overall cost.

6.3.4 Green Shoot Thinning in Vineyards

Like flower and green fruit thinning in tree fruit orchards, green shoot thinning is performed in grapes every year. Green shoot thinning is a task to remove a proportion of shoots growing on horizontal cordons and all the shoots growing on trunks, which is one of the important field operations in the annual life cycle of a vineyard. This operation improves the spacing and direction of shoot growth, which is essential to creating and maintaining healthy and productive crop canopies by improving light penetration and air movement. An appropriate level of shoot thinning will adjust the leaf-area-to-crop ratio and crop load and therefore is one of the greatest determinants of potential yield and quality. When done properly, it also sets the stage for the next year's pruning and training decisions.

When green shoots of grapevines are growing, they heavily occlude each other and cordons, making it extremely difficult to accurately analyze the density of shoots on cordons for the precise removal of green shoots. For green shoot thinning, mechanical thinning machines are being used by the grapevine growers in different states of the USA. Mostly, these machines are mounted on the tractor, and their end-effector consists of a thinning roller on which flappers are attached. When the thinning roller rotates, flappers hit the cordons and remove the shoots from the cordons. The thinning level is controlled by adjusting the height of thinning end-effector to the varying shape of cordons and thinning roller speed by the operator while driving a tractor. However, shoot removal efficiency varies widely (between 10% and 85%) because varying shapes and locations of cordons cause difficulty in precisely controlling the thinning end-effectors against them (Dokoozlian, 2013).

Moreover, various string thinners have been developed and tested to remove the flower clusters for peach trees (Baugher et al., 2010). In these string thinners, plastic strings are attached to the rotating spindle. The thinning efficiency of flower thinning is controlled by adjusting the angular position of string thinner and rotational speed of the spindle.

At the green shoot thinning stage for grapevines, a shoot density of 15–25 shoots/m of cordons is desired to achieve the optimum yield and quality of grapes (Reynolds et al., 1994). If the density is above the desired level, the extra shoots are removed. Moreover, depending on the accuracy of the shoot thinning in vineyards, if needed, later fruit cluster thinning is also adopted for the fine-tuning of crop load. Additionally, not necessarily all three stages of thinning are adopted for each fruit species. For example, for grapevines, more emphasis is given to shoot thinning and fruit cluster thinning, and for apples, blossom/flower and fruit thinning are preferred.

Green shoot thinning, a highly labor-intensive operation, costs growers more than \$650 per hectare (\$265/acre on average), as reported by Dean (2016). If a mechanical shoot thinner is used successfully, the cost could be reduced to about \$25 per hectare (~\$10 per acre). In addition, 1 machine can replace up to 25 workers (productivity 25 h/ha vs. 1 h/ha; Dean, 2016). Therefore, mechanical shoot thinning is essential for the profitability and sustainability of wine grape production. However, currently available machines do not generally offer sufficient precision and speed. Some only focus on removing suckers from the trunk (e.g., Clemens Vineyard Equipment Inc., Rotary Brush).

In contrast, others remove green shoots with an unacceptable level of variability (10–85% shoot removal, Dokoozlian, 2013). The large variation of shoot removal is caused by (i) non-selective removal of shoots by the machine (many non-fruiting shoots arising from latent buds could be retained, while primary shoots bearing clusters are removed) and (ii) the need for manual adjustment of the height of the thinner (thinning heads) to keep it just below the cordon so that most of the shoots growing from the underside are removed. Because of the difficult viewing position, uneven ground surface, and irregular cordon position and orientation, it is highly challenging (sometimes even impossible) to maintain the desired height and orientation of the thinning heads.

Automated thinning using a machine vision system to locate and estimate the orientation of the cordon trajectory would offer a more efficient and effective alternative to mechanical thinning. Majeed et al. (2021) developed a machine vision system and integrated prototype (Fig. 6.13) for vineyards' automated green shoot thinning. First, a machine vision system was developed using deep learning algorithms to estimate cordon trajectories from different growth stages of green shoots (even when cordons are highly occluded with green shoots; Majeed et al., 2020a, b). A Kinect sensor was used to acquire the R-GBD information of grapevine canopies. Then, an integrated prototype was developed that can automatically position the thinning end-effector against the cordon trajectories. The field evaluation results showed that the integrated prototype could precisely position the thinning end-effector within ±1.5 cm of the cordon center. Further improvement in the vision, actuation, and control systems are currently going on to achieve the capability to replace the human operator.

6.4 Artificial Pollination

6.4.1 Introduction

As discussed in Sect. 6.1, profitability for fruit crop producers depends heavily on product quantity and quality – two components determined by the rate of pollination during the brief (but crucial) flowering stage. Currently, growers generally rely on a pollination system that includes renting hives of honeybees (i.e., *pollinators*) and planting extra trees to provide compatible pollen (i.e., *pollenizers*). Even after those

Fig. 6.13 An integrated prototype for automated green shoot thinning in vineyards consisted of a Kinect sensor, platform bed, and thinning manipulator

arrangements, environmental and weather conditions need to be favorable to achieve the desired level of pollination. This traditional approach to pollination is limited by variability and threatened by the changing climate and perennial challenges to the pollenizer-pollinator model. Tree fruit production could not exist as it does today without managed pollinators (i.e., *Apis mellifera*). Yet, in the past several decades, bee colonies have declined by over 40% nationwide.

Furthermore, variability in spring weather conditions affects pollinator activity and can result in smaller fruit set. These emerging issues are complicated by a host of perennial hurdles related to both pollinators (e.g., poor bee activity, uncertainty about how many hives are necessary and where to place them, increasing costs for hive rental, distribution of pollen-borne viruses by bees) and pollenizers (e.g., poor bloom overlap, uncertainty over pollenizer density and distribution, pollenizer trees as disease sources). The result is a multi-billion-dollar industry riddled with uncertainty about the quantity and overall quality of its annual product.

There have been recent efforts to investigate the use of alternative pollenizers and/or insect pollinators. However, this effort is unlikely to yield sustainable improvements in the long term, as more crops are needed to feed a growing world population. Alternatively, mechanical and robotic approaches (e.g., ground sprayers, UAS-based pollen spraying, robot bees, robotic precision pollinators) are currently being developed and evaluated in orchards that are expected to yield solutions that minimize the biological variability of the current pollinator + pollenizer model.

6.4.2 Mechanical and Robotic Pollination Techniques

Researchers worldwide are developing different types of artificial (or mechanical) pollination techniques for various types of crops. Both aerial platforms and ground platforms have been used in developing these techniques. UAS-based systems generally use small platforms and apply a bombing technology to spray pollens on canopy surfaces from the top. Alternative to these UAS platforms is bee-line flying robots developed and tested by Berman et al. (2011) and Abutalipov et al. (2016). These tiny platforms mimic bee behavior and have shown potential for pollinating fruit crops in orchards using a swarm robotics concept.

Artificial pollination using ground vehicles generally uses similar systems to agrochemical application systems. The machines are often designed to spray pollen suspended in a liquid or dust medium to target canopy areas. Electrostatic spraying and other spraying technologies have been tested to optimize the type and size of nozzles, operating pressure, flow rate, carrier medium, and distance to bloom so that the level of pollination and fruit set could be achieved. One such study was carried out recently at Washington State University by Whiting (2017) (Fig. 6.14). An

Fig. 6.14 An electrostatic sprayer retrofitted by Dr. Mathew Whiting and his team at Washington State University to apply pollens, being evaluated in a cherry orchard in Prosser, WA. (Picture by TJ Mullinax/Good Fruit Grower)

electrostatic sprayer was tested to broadcast pollens onto cherry canopy surfaces, which showed increased effectiveness in depositing pollens on flower stigma than natural pollination with bees.

Similarly, Gan-Mor et al. (2003) and Gan-Mor et al. (2009) developed and tested electrostatic pollen sprayers to artificially pollinate almond, date, kiwifruit, and pistachio. Such mechanical pollination technologies have been demonstrated to be effective and useful in various production needs and show potential to be an alternative to the natural pollination process. In addition to an evaluation in research programs, there have been some commercialization efforts to bring this technology to commercial orchards (e.g., a mechanical blower system commercialized by PollenPlusTM, New Zealand).

The mass artificial pollination techniques discussed above are simpler and easy to operate. Still, they are inefficient as they broadcast pollens to wide canopy regions without regard to where the target flowers are. To address this challenge, researchers are developing machine vision and robotic systems (with manipulators and end-effectors) for targeted pollination of desired flowers (e.g., Fig. 6.15). Various studies on detecting/segmenting flowers and flower clusters in fruit trees have been discussed earlier in the "Precision Thinning" section (see Sect. 6.3.2 for more details). In addition, there have been a few specific efforts to develop robotic pollination systems for fruit crops. One such study was conducted by Duke et al. (2017) and Barnett et al. (2017). Their robot was evaluated in kiwifruit using an autonomous platform and a spray manipulator. The vision system included an RGB camera and a CNN-based image processing technique for flower detection. Field evaluation results showed that

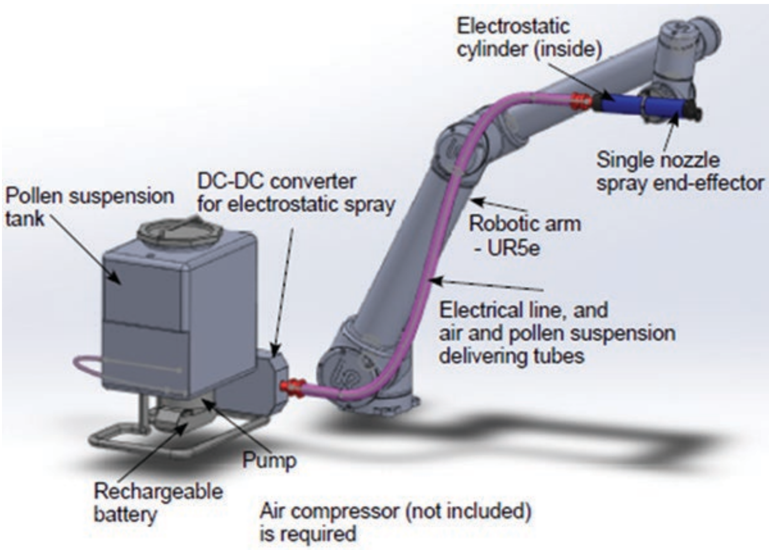

Fig. 6.15 A schematic of the robotic precision pollinator system currently under development at Washington State University. (The project also includes researchers from Pennsylvania State University)

the flower detection accuracy was >70%, and more than 80% of the detected flowers were pollinated with the robotic system. Similarly, Yuan et al. (2016) presented a robotic solution for pollinating tomato flowers in a greenhouse. This robotic system was mounted on a mobile platform and consisted of four-DoF manipulators and a spray nozzle as its end-effector. The system used a binocular camera to capture flower clusters' images, and color and size features were used to segment the clusters out. The robotic system can recognize 80% of the flower clusters with at least two flowers and pollinate (spray the pollen) with a 69.6% success rate.

When successfully adopted in commercial operations, the targeted application of pollens with robotic machines – rather than spraying trees en masse – will play a critical role in the efficient use of pollen and may increase deposition, improve crop-load control, and minimize off-target drift (Patel et al., 2016; Sparks, 2014; Dung et al., 2013; Bechar et al., 2008). These innovative technologies also can alleviate growers of considerable risk associated with insufficient pollination as it relies currently on natural processes that are in decline, sensitive to environmental conditions, and amenable to distributing viral diseases. The success of the robotic pollination will also avoid complexity in the cropping system (for planting pollenizer trees and hiring beehives) and increases the planting area for target crops (e.g., apples).

The development of practical robotic systems for thinning faces various challenges, like the robotic thinning systems discussed in Sect. 6.3.2. One of those challenges is the capability of the vision system to identify the king flower to perform pollination at the right window when only the king flower is open in most of the floral buds. The challenge originates from the fact that the blossom in fruit trees opens over a few days to a couple of weeks. In comparison to the continual presence of natural pollinators like bees over the flowering window, artificial pollination is generally a one-time operation, thus limiting the opportunity to pollinate sufficient flowers. However, suppose there is a possibility of choosing the window smartly. In that case, it could provide an excellent opportunity to implement an effective crop-load management via artificial pollination using mechanical or robotic means. More studies on this aspect would be essential in the future.

6.5 Challenges and Future Directions

As discussed in the earlier sections, there has been a wide range of research and development activities worldwide to develop automated and robotic solutions for precision and selective crop-load management operations. Some private companies such as Vision Robotics (San Diego, CA) and ATRIA Innovation (Nave, Spain) have also been developing robotic pruning, thinning, and/or pollination solutions. However, no commercial success has yet been achieved in crop-load management operations. In general, robotic operations in the agricultural fields are challenged by three factors: (i) uncertain, variable, and complex canopy, lighting, and environmental conditions; (ii) plant and produce damage; and (iii) slower speed, high cost, and lack of adoption (Karkee & Zhang, 2021). For example, flowers grow in uncertain canopy locations in tight clusters, whereas tree branches vary widely in shape, size, and location over space and time.

Many studies have been conducted in the area of perception of fruit tree canopies for various crop-load management operations (e.g., pruning and thinning) using different kinds of sensors/cameras and image processing techniques. However, many of these past studies utilized some environment control mechanisms to improve uniformity and minimize the uncertainty in the canopy lighting conditions. For example, some of these studies used canopy covers (Botterill et al., 2017). Other studies were carried out in laboratory conditions to avoid direct sunlight, provide uniform illumination using artificial lighting, and remove complex backgrounds from the desired tree canopies. Though such amendments helped improve the performance of the vision system in the orchard environment, they added complexity to the overall system. They reduced the practical feasibility of commercial adoption of robotic crop-load management techniques in field conditions. Advancement in AI tools such as deep learning has, to some extent, addressed this problem and has improved the accuracy and robustness of machine vision systems both in indoor and outdoor conditions. Further development and adoption of deep learning-based and other robust, efficient, and reliable machine vision systems remain critical for developing practically applicable and commercially viable robotic/automated systems for crop-load management.

It is also noted that commercial viability can further be improved by developing multipurpose robotic machines. There has been a great advancement in robotic picking machines by researchers like the authors of this chapter (Silwal, 2016; Silwal et al., 2017) and private companies, such as FFRobotics (Haifa, Israel). However, those complex and expensive machines would be operating in the field only about 3 months over the year. If such a machine could be designed to perform multiple field operations ranging from canopy management (e.g., tree training), crop-load management (e.g., flower thinning), and pest control (e.g., targeted application of pesticide) to crop harvesting by only replacing the end-effectors of the machine in a modular fashion, the high cost of such machines could be more justifiable, and commercial adoption could be accelerated.

The structure of the fruit tree is complex due to its biological nature. Fruit tree growers in recent decades moved toward the trellis trained structure because of the possibility of achieving a high density of fruit trees, high yield, and quality of fruit, which also opened up the opportunities for the mechanical and robotic operation for various field operations (Majeed et al., 2020c). Simplified training systems make pruning, thinning, and other crop-load management operations viable. For example, UFO cherries offer a system where pruning can be, theoretically, a mass removal of all the secondary branches growing laterally from the vertical offshoots. In such a case, a pruning system could now be simplified to include a round cutter that can follow the trajectory of the offshoot from bottom to top so that everything growing laterally would be removed without regard to their location and size.

Similarly, all the secondary branches growing vertically above the horizontally trained branches could be removed using a chainsaw end-effector in the formal apple orchards. These opportunities indicate that further simplification of canopies, particularly to keep them narrow and have a simpler canopy skeleton, would allow for simpler, objective crop-load management strategies (e.g., objective pruning rules) and relatively simpler robotic manipulation (e.g., linear access to thin flowers). These opportunities can lead to more effective and commercially viable robotic solutions for various crop-load management operations.

Studies found that various tasks, including perception, decision-making, and field implementation of the robotic operation, have unique challenges in the orchard environment. For example, Karkee et al. (2014) found that implementing various pruning strategies, such as removing diseased branches, was not easy for a robotic system due to the lack of a desired sensing system. This finding indicates that precision crop-load operations such as pruning, thinning, and pollination of fruit trees may best be achieved through human-robot collaboration, where human performs tasks requiring strong sensing capabilities, human judgments, and complex manipulation. In contrast, robotic systems perform tasks that can be performed with efficient machine vision systems, objective rule-based decisions, and simpler (e.g., linear) manipulation. Bechar and Edan (2003) found that a proper level of human-robot collaboration could substantially increase fruit detectability in orchards, applying to flower and branch detection and localization. One essential requirement for such technology is to have a proper training method for robots to acquire human knowledge in in-scenario data.

For real-time field operation with desired precision, robotic solutions for orchard operations require high-resolution imaging and image analysis, fast sensing systems, effective end-effector techniques, and fast and low-cost manipulation. Newer, low-cost sensors, AI tools such as deep learning, modular robotic technologies, and increased capability and decreasing cost of computation (e.g., graphics processing units) are providing new opportunities to develop faster, reliable, and robust robotic solutions that could soon lead to commercially viable systems for selective pruning for fruit trees.

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Chapter 7
Mechanical Harvesting

Daniel Guyer

Abstract Mechanical harvest of tree fruit and grapes involves a number of nearly endless, as well as highly variable, factors and challenges, much in part due to the fact that biological systems are not "ideal" systems under which mechanization and automation have traditionally been successfully developed. This chapter is a general overview of many of the fundamental factors and challenges that surround mechanical harvesting and the development of mechanical harvesting systems and provides some examples of various current and possible future concepts.

7.1 History, Perspective, and Evolution

The push and need for mechanical harvest in fruit production can basically be broken down into two purposes – the first being to improve production efficiency and profitability and the second being concerns and challenges surrounding labor availability – with there certainly being some overlap. The latter purpose has been partially cyclical, at least in the USA, and has at times been politically based. For instance, the Cesar Chavez movement around the 1970s and then diminishing labor availability due to changing worldwide economic situations and immigration factors rising to a much higher issue level beginning around 2000 are examples that have led to heightened attention and funding push to develop mechanized fruit harvest technology and systems. Harvest mechanization not only helps to reduce the need to perform physically demanding labor tasks but also assists growers, especially those of larger scale, to complete harvest operations during the optimal harvest window for maximizing quality and yield and thus profitability.

Historically, most hand harvest has been very effective for multiple reasons. High capital investments for machinery development, as well as for the grower to

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purchase, have led to lobbying for easier access and inexpensive labor (Sarig, 2012). It appears, however, that the crossover point has been reached for more and more commodities due to technological advancements, economies of scale, and the changes in the labor environment. A general qualitative example is shown in Fig. 7.1, and such lines and crossover points will vary by operation size.

The dividing line between the definition of manual and mechanical harvest varies as systems exist that are "harvest-assist," whereas a portion of the duty required of a traditional fully manual/human system is mechanized. At the commercially available level, these include harvest-assist systems or components which do the mundane tasks not requiring sophisticated manipulation or intelligence, such as platforms that move and position manual pickers within the orchard and/or systems that convey the fruit between the picker and the collection bin, thus allowing the time spent for highly intelligent and articulate aspects of selecting, locating, and removing the fruit, all of which the human is so effective and manipulative in doing, to be maximized. These systems, as they are and as "tools," have proven highly effective as well as being potential important steps or components toward possible full automation. The focus of this chapter is directed on mechanical harvest systems that remove the fruit without physical contact between the fruit and a human.

Successful transition from manual labor to mechanized systems involves a broad "systems approach" integrating (1) tree/plant adaptation, (2) machine capabilities, and (3) postharvest (in field or after) sorting and handling. Such systems must also look beyond just the integration of factors directly related to the harvest aspects, to the broader scope of overall production and final product factors and economics. This would include how might changing the plant system to better align with the mechanical and electronic systems affect total fruit production/yield and quality, tree longevity, and subsequent year(s) fruiting or other production operations such

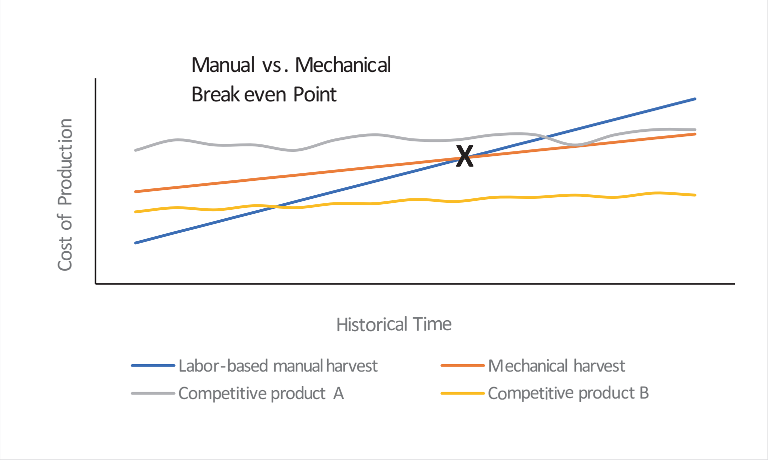

Fig. 7.1 Generic depiction of evolutionary convergence of breakeven point for mechanical versus manual harvest utilization in relation to alternative competitive crop production costs

as disease and pest spread and control. The solutions, to be successful, must address the production bottom line with a broad perspective over the life of an orchard. Developments of mechanical harvest systems to date have come from commercial companies where several systems exist for processing-destined fruits; academic-based research and development which is significantly focused on fresh market automation/mechanization systems; and growers who are amazing innovators in their own right and quite often in combination or joint venture with one or more entities.

Postharvest sorting systems are likely an important and critical tangential technology with the implementation of, or transition into, mechanical harvest as quality issues/damage and variability of maturity are likely to be much greater in mechanically harvested product. Thus, parallel implementation of postharvest technology is needed to support mechanical harvesting. Fortunately, postharvest sorting is well advanced with the exception of some internal detection, and mechanical harvest issues would mostly be external or at the surface of the commodity (bruising/cuts/tears/color). Sorting and leaving culls in the field is potentially an option as part of mechanical harvest; however, everything must be taken into consideration as an overall system, as leaving culled fruit in the orchard/vineyard could lead to pest or disease issues.

Fresh market mechanical harvest will only occur successfully when plant characteristics and machine designs are integrated into compatible systems (Peterson, 2005), which minimize impact instances of fruit to fruit and fruit to limb while detaching and while falling and fruit upon fruit and fruit to catching surface at the point of contact with catching system.

7.2 General Considerations, Goals, and Challenges Associated with Harvest Method Selection

Several factors need to be considered in mechanical harvesting, which will help determine the goals and tolerances and dictate the design.

A. End use: Is the fruit destined for fresh or processing use? This will usually dictate the level of fruit quality that must be maintained. While damage to processing-destined fruit can generally be tolerated to certain levels, there are limits such that the yield of the processed product is not adversely affected. An example is with tart cherries, where the fruit must not be damaged to a level such that juice and pulp are lost, and equally important, the fruit must maintain its shape integrity such that it seats itself properly in the pitting machines, so pits do not end up in the final product. Grapes for processing can tolerate significant damage as long as desirable juices are not lost, as the grapes are destined to be crushed anyway.
B. Single- or multiple-pass requirements: Does the fruit on a given tree/vine ripen with a high level of uniformity such that a single pass of harvest is sufficient, or

must the harvest process take into consideration the ability for multiple harvests of the same plant over the harvest season and thus not jeopardize immature fruit?

C. Economic feasibility and breakeven points: What rates and at what cost per unit must the mechanical harvesting system achieve? The cost per area (acre/hectare), or per weight unit, of different harvest approaches is highly variable, and the breakeven point of incorporating manual or mechanized systems (or something in between) will vary along with the parameters used to conduct or base the analysis. For example, harvest system yield loss (to ground or left on plant which has been studied to show ranges from approx. 5–10% in grapes) will generally cause the breakeven point for mechanical harvest to rise with an increase in price of the commodity as will increases on fixed and variable machine costs. Studies exist, for example, Jobbagy and Kristof (2018), to show some of these relationships and the range of cost and reasons for such. It suffices to say studies show the breakeven points will vary by size of operation, cost of labor, fixed and variable machine costs, and cultivar (foliage density, height, location of clusters, maturity uniformity) and even from year to year within a given operation due to growing conditions or maturity of fruit. In general, breakeven curves, such as shown here in Fig. 7.2, can be quantitatively developed for each cost parameter, but the overall decision is much more highly dimensional.

D. Food safety: Is a goal of the harvesting system to reduce human contact, and/or are there other food safety considerations that must be worked with? Are the concerns over food safety higher or lower for mechanical harvest vs. manual harvest for a given commodity?

E. Residuals in harvested fruit: How much non-fruit material can be tolerated so as not to impact the final product? The impact of residuals such as leaves, stems, and any other material other than the fruit (commonly referred to as MOG in grapes) and poor quality or infected fruit on final product quality such as wine has been studied with mixed results. Generally, minimizing such material is desirable; and whether manual or mechanical harvest results in higher percentages of such is also shown with mixed findings in studies.

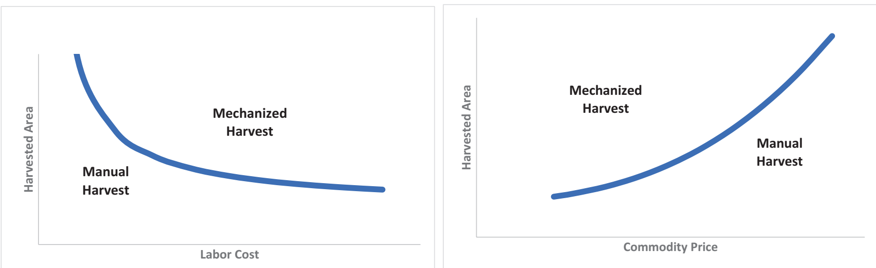

Fig. 7.2 Qualitative example of breakeven dividing curves for harvested area against labor cost (left) and harvested area against commodity price (right)

F. Optimal harvest window/timing: Can product quality, and therefore net returns, be increased by the ability of mechanical harvest to narrow the harvest window and harvest fruit at the optimal point of maturity? This is a quite universally acknowledged benefit in most fruit industries.
G. Plant tolerance: How much damage from mechanical systems can the tree/vine tolerate to avoid insect and disease and other acceleration of tree mortality or damage to future fruiting?
H. Night operation: Can mechanical harvest lead to night operation and extend working hours for harvest and/or help maximize quality and reduce field heat removal costs through harvest during cooler nighttime temperatures? This also relates to optimal harvest timing, as noted in F above.

7.3 Factors and Variables That Influence or Are Associated with Fruit Detachment, Mechanical Harvest, and System Development Potential

7.3.1 Plant Physiology

Multiple factors exist related to plant physiology and its relationship with mechanical harvesting; the most obvious is, of course, the separation of the fruit from the tree or vine. This occurs naturally/physiologically over a period of time due to abscission of the fruit from its stem and/or the stem from the plant. There is considerable research and understanding of this process historically, both from the biological and mechanical aspects, as well as how this natural process can be influenced by chemical (often hormonal-based) application intervention. Such intervention, whether chemical or through plant management (pruning, support structure, etc.), supports two things:

(a) Narrowing the window in which the fruit are physiologically ready/able to detach and thus supporting single-pass harvesting. This window can also be influenced by tree/plant "design" and crop management techniques. If all fruit are subjected to the same "micro-environment" within a given plant, this will reduce maturity variability on the tree and within the orchard/vineyard and increase uniformity in harvested product fruit maturity.
(b) Reducing the force/energy required to separate the fruit from the stem, thus leading to less energy input which subsequently leads to less potential plant damage and less kinetic energy (motion) of the fruit. Kinetic energy tends to cause damage from higher energy impacts, during and following any mechanized induced fruit detachment process.

7.3.2 Coupled Physiological and Physical

The following are parameters related to the fruit/plant which cause variances in fruit motion with the same induced mechanical excitation/vibration:

- Size of fruit.
- Stem length.
- Stem stiffness.
- Fruit location on plant in relationship to harvest energy impact location.
- Plant structure and age, including limb size and stiffness, and pruning.
- Fruit crop load (yield) on plant.
- Foliage density and limb structuring (willowy or stiff or between).
- Fruit growing system, for example, trellis and posts, and the effects it has on potential damage to harvester or trellis system on top of vibration/oscillation characteristic influence.
- Cultivar variability (maturity, firm fruit, limb length, and stiffness).

7.3.3 Mechanically Induced

The following are parameters related to the applied mechanical force to induce detachment:

- Amplitude of impact/vibration.
- Frequency of impact/vibration.
- Direction/pattern of excitation.

7.3.4 Others

- Orchard/vineyard topography which will impact fruit motion/flow on catching components and conveyors.
- Stem or stemless final product.
- Integrity/quality of final harvested fruit.
- Minimizing damage to tree/vine in general and especially future fruiting sites.
- Uniformity of fruit maturity and single or multiple harvest passes (as it relates to how vigorously to remove fruit).
- Fruit removal efficiency necessary.

Each of these influences the detachment of fruit, or the design approach toward such, as part of a mechanical harvesting system for a given fruit commodity, and compromises are the norm and will vary by user and commodity and the specific economics for a particular operation.

7.4 Engineering Concepts, Theory, and Biological Variability Behind Fruit Removal

Whether hand/human, mass, semi-mass, or automatic/robotic-based harvest, detachment forces come into play unless the stem is cut, whereupon locating and cutting the stem is a different venture/process. Numerous structured laboratory as well as field-instrumented/field-measured studies (e.g., Cooke & Rand, 1969; Garmen et al., 1972; Du et al., 2012; Torregrosa et al., 2014; Zhou et al., 2016) have been conducted and models and theories proposed, related to quantifying the dynamics and specific forces required, and optimal, for fruit detachment related to mechanical harvesting. Examples of such approaches and dynamics include:

1. Minimal fruit movement with rapid tensile force along the stem.
2. Unstable/radical movement causing stem bending, etc.
3. Subjecting the plant to a series of chaotic motions/conditions to cover the range of bio-variability and ultimately a gamut of optimal detachment dynamics even within a given single plant.

7.4.1 Theoretical Types of Dynamic Motions and Subsequent Static and Dynamic Forces Occurring during Vibration/ Shaking or Other Forces Applied to the Tree/Vine During Mechanical Harvest

A. Tensile: A tensile force in this context is considered a force applied along the direction of the stem, i.e., pulling the fruit "straight" off. In this situation, all biological attachment mechanisms remaining at the abscission zone/point and holding the fruit to the stem, or the stem to the plant, are acting together in parallel, and thus a higher force threshold is required to detach the fruit. However, with a dynamic motion applied along the direction of the stem, the fruit weight can be used to help create the force to overcome the force required to detach. Additionally, for some fruit, such a force can reduce other movements of the fruit and thus minimize the potential for additional energy of motion, which can result in higher or multiple quality-reducing impacts during or after the detachment.
B. Pendulum/centrifugal: Similar force along the stem as tensile but caused by centrifugal force during swinging. Additionally, some degree of "whip" can occur at the end of the swing, creating some amount of bending at the abscission zone. Stem length and stiffness are two of the factors that play a role in this motion and the forces generated during excitation.
C. Torsional: In this situation, the fruit is turned or pivoted about the stem axis, and "shear forces" are created at the abscission zone to which the tissue may be less resistive, thus allowing easier removal. The plant is not evolved to strongly resist

this unnaturally occurring force. However, generating a solely torsional force is challenging other than by manual hand harvesting or possibly robotic harvesting. The resulting lower force required to remove the fruit with torsional motion can lead to less fruit or plant (such as fruiting spur) damage.

D. Bending/tilting: This motion or situation, in theory, involves more of a "progressive breaking" of the natural attachment strength of the fruit at the abscission zone. The tilting or bending subjects one side of the abscission zone to a greater force, thus resulting in the yielding of attachment. This progresses across the abscission zone resulting in lower maximum force required to remove the fruit and potentially less damage to the fruit and/or plant. This is a common hand-picking motion and is a motion that is either directly or indirectly created at some point in most currently successful mechanized harvest systems.

Each of these motions/forces (Fig. 7.3) can be theorized, studied, and tested. But, in the end, there are multiple actions happening simultaneously when dealing with field applications. Additionally, this is all occurring in a biological system in which there is minimal consistency or repeatability to speak of; thus, theory and controlled tests are only partially applicable. However, modeling can help be a predictor for design.

Fruit motion and detachment have been modeled extensively, but there are biological variability and many more degrees of freedom that take over and prevent the situation from being an "ideal" system during the actual field harvest. Often an experienced trunk shaker operator will make optimal adjustments on the fly. Short bursts tend to create a range of dynamics in the tree and to the fruit, and thus effective detachment is more likely to be achieved because somewhere within that range, an optimal removal force/motion, or a combination thereof, will present itself. Additionally, it can be theorized that, in practicality, multiple smaller movements and/or forces can potentially loosen and ultimately detach the fruit due to repetitive fatigue, much in part similar to yield (breaking) in metals after bending back and forth with repeated cycles. Supportive of this theory is fruit detaching from the plant during a wind event where both physical and physiological loosening at the abscission zone occur.

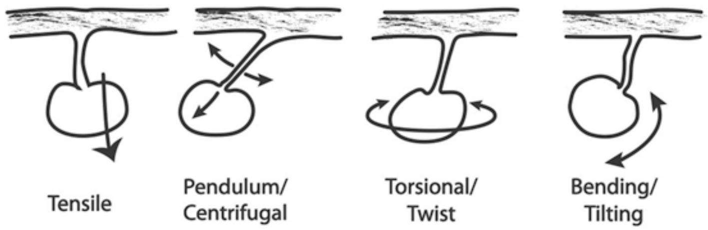

Fig. 7.3 Theoretical detachment modes. (Figure by Virginia Rinkel)

It should also be noted that the optimal detachment motion might not be best to maintain high fruit quality. Therefore, compromise may be required, and this is again an example of the need to consider the development of a mechanical harvester within the context of the overall "system." If not considered as a systems approach, there may be initial unit operation success but long-term failure.

7.4.2 Fundamental Concepts of Mechanical Harvest

The initial categorization of mechanical harvesting relates to whether the system is based on direct or indirect energy transfer to fruit, i.e., does a physical member of the harvester directly impact/touch the fruit or is energy from impact or vibration transferred through the tree or vine and to the fruit and stem?

An overview of basic mechanical harvest systems is as follows:

7.4.2.1 Trunk Shaking: Indirect Detachment

Trunk-based shaking systems are based on a single clamping event to the main trunk of the tree, and the entire tree is given a shaking motion in a single plane. The "clamp" is generally a heavy floating head that is suspended from the harvester (often under a catching frame; see later section) that squeezes two large pads against opposing sides of the tree. The shaking motion/energy is induced by a hydraulically driven spinning offset weight, also within the suspended head. Energy/vibration/motion is transferred from the trunk up through the primary and secondary branching, thus inducing physical motion of the fruit and/or relative motion and forces between the fruit and the tree/bush. The "pads" will vary in style but have been cylindrical hollow rubber horizontal "pillows" filled with ground walnut shells so as to be able to form to the tree shape and fit with good surface contact, and the shell material will not easily break down due to its hardness. Newer pads of hollow, thicker walled rubber cylinders are now seen on machines (see Fig. 7.4). These pads are usually draped with two layers of conveyor belting with grease between the layers to provide slippage between the belts instead of at the tree surface and thus minimize damage to the tree bark and cambium. Much study and evolution have occurred on trunk shaking clamp styles, clamping pressure, and motion to minimize tree damage and optimize fruit removal. A skilled operator remains important! The duration, frequency, and amplitude of the shaking can be controlled and adjusted during the harvest to minimize tree and fruit damage and maximize removal. Hormone-based sprays are commonly carefully timed ahead of harvest date to induce loosening of the fruit attachment/abscission zone, so minimal force is required to detach the fruit. Trunk shaking has become "semi-continuous," with intermittent stops at each tree.

Fig. 7.4 Trunk tree shaking head

7.4.2.2 Limb Shaking: Indirect Detachment

This concept, like trunk shaking, transfers energy and motion to the tree but on a limb scale rather than a whole tree, and thus, since it deals with less tree mass, the systems require less size and energy. The positive aspects of limb shaking are the lower capital cost of the shaking system and the ability to potentially move the catching aspect of the mechanical harvest closer to the fruit, such as directly under the limbs, so as to reduce drop damage. Additionally, because only limbs are being shaken, the opportunity exists to induce the vibration/movement in a vertical motion or a horizontal motion or at another controlled angle to optimize fruit removal from a given limb. With limb shaking, the potential to cause trunk damage is eliminated (although limb damage could occur), and the energy is induced closer to the target (fruit) and not lost through travel through trunk and branching, thus giving a bit more control over the actual motion and forces at the fruit location on the limb. The negative aspect of limb shaking is the need to move around the tree and position so as to be able to shake every limb. Some limb shakers are handheld by humans, and others are attached to the machine. Limb shakers are rarely used and have become obsolete with successful newer alternative systems and large-scale orchards.

7.4.2.3 Canopy Shaking: Combination (Hybrid) of Indirect and Direct Detachment

Canopy shaking presents itself in several approaches or forms. One form is vertical shafts/spindles with long, firm tines, often fiberglass and numbering in the hundreds, protruding radially outward. The spindles, usually one on each side in an over-the-row side enclosed machine, are passive in rotation and feed the tines into the tree/plant canopy as the harvester travels over the row (see Fig. 7.5). A vibrational inducing system consisting of rotating off-center weights is mounted at the top of each of the vertical shafts causing the spindles to vibrate back and forth while engaged within the canopy, resulting in lower energy per contact point than a trunk or limb shaker, but many, many more contact points. The amplitude and frequency of vibration can be controlled with the offset and speed of rotation of the weights. The density of tines on each spindle is a variable and can be altered to optimize for the commodity and/or growing system. These spindle shakers are found in bush-type plant systems such as bramble harvesters and blueberry and are being evaluated or are available for some tree fruits such as cherries and oranges. They are a combination of indirect and direct energy inducing as the tines make hundreds of contacts with limbs and cause shaking of the limb; but also, with the high number of tines, it is common that a tine will directly contact the fruit and dislodge it. In tree systems where more "woody" plant material exists, the tines can cause plant tissue damage, which may or may not be a concern depending on plant type.

A second canopy shaking form is less engaging and more an entire moving or swaying of the plant/bush back and forth, sometimes termed pivotal (see Fig. 7.6). The concept of removal here is twofold. First, there are inertial forces transferred to the fruit as the entire plant is swayed/pivoted back and forth in a rapid reversal of direction, and second, there is considerable "abrasion" that can occur as leaves and small branches move about during the plant swaying, and thus the fruit can be directly contacted and dislodged. The plant movement is induced by drawing the plant through a narrow opening between several sets of horizontal bars or bow rods that synchronously thrust the plant back and forth perpendicular to the row and travel. The aggressiveness of the system can be tuned through the spacing between rods, stroke length, frequency of stroke, etc. This system is effective and common in grapes and blueberries. A significant overall "systems" concern with canopy shaking is the possible enhanced spreading of disease throughout the orchard as spores can carry on the machine from one tree or area to the next.

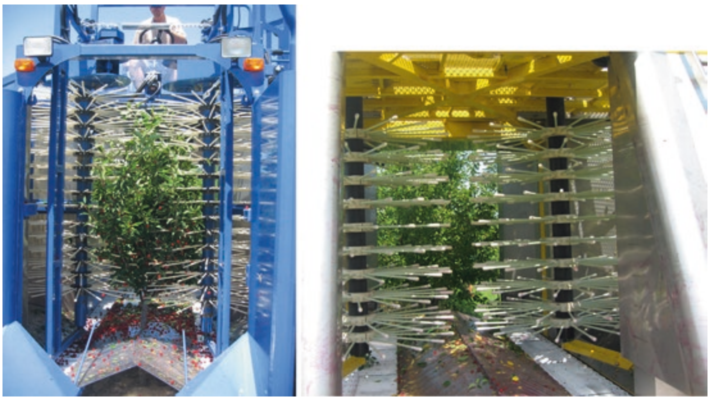

Fig. 7.5 Vertical spindle canopy shaking harvest concepts: (**a**) commercial blueberry harvester tested on small tart cherry and (**b**) spindle harvester developed for small trees specifically. (Photos by Daniel Guyer)

Fig. 7.6 Internal chute of pivot or sway canopy mechanical harvester. (Photo by Daniel Guyer)

7.4.2.4 Air Blast: Combination (Hybrid) of Indirect and Direct Detachment

This approach uses high-velocity air, which is usually pulsed in some fashion within a semi-enclosed over-the-row chassis, to cause the fruit itself, or the plant as a whole, to move and shake and create fruit detachment motion and forces (see Fig. 7.7). This system covers a range of basic concepts in that the mechanism inducing the movement, albeit air, can come in direct contact with fruit and cause it to detach, but also the air is causing the entire plant to sway or move in erratic motion causing plant tissue to interact and detach fruit through direct physical contact as well as cause movement of the limbs which subsequently moves the fruit and creates dynamic removal forces. This system initially seems to idealistically be an approach of high potential success, including potentially less fruit and/or plant damage. Systems have been developed but have not been adopted as optimal forces for removal do not seem to be able to be developed in the process. While the plant movement may appear rather "violent," the movement is ultimately gentler, and the slight "jerking" or "snapping" motion needed and created in rapid directional changes does not seem to be generated in air blast systems. The fruit that is removed is done so via abrasion/contact between plant parts. Additionally, much of the energy put into moving the air is not efficiently utilized, and the leaves absorb and/or block a lot of the energy, thus resulting in rather poor energy efficiency.

Fig. 7.7 Internal chute of pulsed air blast canopy shaking trial concept. (Photo by Daniel Guyer)

Each of these four basic concepts has advantages and disadvantages, as noted. One thing common to each is that fruit quality and, in part, a level of selective harvest can be addressed via the amount of energy applied to the tree/vine/plant. If the economics, logistics, and plant are such that a single-pass harvest is desired or required, then higher energy and aggressiveness can be implemented, whereas it is also possible to more gently introduce energy such that only the ripest fruit is detached each pass over time and the remaining fruit are minimally damaged. With proper "tuning" of the system and careful operation, there is potential, especially with canopy spindle harvesters, to harvest fresh market-destined fruit. Additionally, canopy shaking and air blast spraying allow for continuous flow harvest, which is an easier concept for the operators.

7.4.2.5 Catching Systems

In general, "catching" the fruit after detachment is as important of a challenge as separating the fruit from the plant. Catching systems must attempt to minimize fruit damage and minimize loss of harvested fruit to the ground. Catching concepts vary with the type of detachment system. For trunk shakers, the catching system must encompass the entire surface area under the tree plus an even greater area as some fruit tends to be tossed a bit beyond the area under the tree when subjected to shaking. Dual roll-out tarps, one on each side of the trunk, that extend under the tree from one side of the tree to the other and then are mechanically drawn in toward a collection conveyor after shaking, with workers holding the distant side, is one lower capital cost concept, but one which has become rather obsolete due to speed of operation and need for several additional workers (see Fig. 7.8). There can also be fruit damage issues as the shaking machine is separate and must drive onto the tarp each time and will roll over fruit when it retreats. There is also some tendency for some fruit to be squeezed in the tarp retraction process.

The "one-man" machine concept combines the shaking head and the catching tarp in one machine and is operated by a single individual (see Fig. 7.9). The harvester has an extended front end that the operator drives under the tree and positions the shaking head around the tree trunk, after which a catching tarp unfolds as two half circles and encompasses the entire underside of the tree, looking much like an inverted umbrella. The shaken fruit falls into the tarp and funnels to the center under the tree, where the harvester has conveyors to move the fruit to the back of the machine and into holding tanks. The machine then draws the umbrella tarp back into folded position, releases the shaker from the tree, pulls back into the row between the trees, and advances to the next tree. This harvester works well with the positive aspect being that only one operator is required; however, the negative aspect is that significant time is required in reversing and unfolding and refolding, etc., between each tree. Such an approach could be considered a semi-batch process that harvests at a rate in the range of one tree per minute, but something that has been an appropriate harvester for smaller acreage growers.

Double-incline harvest systems are most popular and efficient if the grower is of acreage size, as most are, for the economics of scale to allow for this system. This system requires two separate machines, and each has large tarps sloped in basically a single plane, from beyond the edge of the tree down to the trunk where the shaker is engaged and is long enough to cover the width of the tree (see Fig. 7.10). The tarps are permanently drawn/suspended over metal framing and covering one-half of the area under the tree, and the framing can be partially retracted from the tree trunk for travel to the next tree. One of the two machines travels down the row on one side of the tree and has a conveyor the length of the tarp at the bottom under the

Fig. 7.8 Roll-out tarp catching concept. (Photo by Bill Klein)

(a) (b)

Fig. 7.9 "One-man" harvester: (**a**) folded moving from tree to tree and (**b**) in unfolded position during trunk shaking. (Photos by Daniel Guyer).

(a) (b)

Fig. 7.10 Double-incline trunk shaking system: (**a**) closer view with shaking mechanism visible and (**b**) more distant view showing overall size. (Photos by Daniel Guyer)

tree into which the fruit from both machines is collected. The second machine has an inclined surface as well on the opposing side and also carries the shaker head under the tarp, which extends a short distance to the trunk and back for each tree cycle. Detached fruit falls from the tree and rolls down the tarp surfaces and into the conveyor, where it is then conveyed into the collection tank. These tarps are quite taut but have some "give" to help reduce fruit damage. The tension on the tarps can change with temperature and cause issues. This is a system common in tart cherries destined for processing and is effective because it is semi-continuous, and trees can be harvested at a rate of around four trees per minute depending on conditions and crop load. The positive aspects are the rate at which experienced operators can harvest, while the biggest drawback of double inclines is the initial cost and maintenance of two machines.

Canopy shaking requires catching systems that can function continuously. This is most commonly accomplished with a tree/plant seal near the base of the plant and is constructed of many overlapping flower petal or fish scale-like Lexon or nylon plates that extend in the center about 1/4 of the harvester's internal width from each side. These plates are spring-loaded and sloped from the center toward the side, continuously forming around a tree trunk or vine, or plant stem as the harvester passes (see Fig. 7.11). When not engaged with the plant, the plates/scales from each side meet in the center to divert all falling fruit to the conveyance system under the tree along the outermost edge of the chute of the machine. With the continuous overlapping of the plates, regardless of their default or pushed back position, the catching surface/zone remains nearly fully sealed/covered. It is a very effective system as long as there are no weeds or "outlier" plant stems, causing the plates to open further than necessary. The advantage is the excellent seal that occurs and captures fruit and the ability to operate continuously. The challenge with this catching system is it is unidirectional and you cannot reverse direction and must continue to the end of the row or an opening in the row to be able to leave the row for any reason. Additionally, because the angle of the plates is fixed to slope toward the conveyors on flat ground when on sloping terrain, the plates on one side become flat, and fruit will not roll and can build up and be damaged or find its way to the ground during opening and closing of the plates around the plant. Self-leveling machines reduce this issue, and some newer catching systems are minimizing the size of the plates and incorporating short-distance conveyors to carry the fruit from the plates toward the primary lift conveyors, which is a more active rather than passive approach. It solves a problem but adds cost and maintenance. Fruit in a canopy type of system generally fall rather short distances at any one drop to the catching surface as it is dislodged from the plant and has to fall through several small distances down through the plant before making the final drop to the catching surface.

A researched future concept has been attempted, with the thought to develop some form of terracing within the tree or plant and incorporate catching surfaces

Fig. 7.11 Tree seal "fish scale" fruit catching surface for canopy shakers: (**a**) showing full shoot and conveyors and (**b**) close-up of scale engagement with tree. (Photos by Daniel Guyer)

under each "terrace" to bring the catching surface/mechanism closer to the fruit and therefore minimize drop distance.

7.5 Effectiveness: Examples of Current, Obsolete, and Unsuccessful Systems

7.5.1 Cherries

While some research and development efforts have addressed the potential for mechanical harvest for fresh market sweet cherry, most mechanical harvest for cherry is done with one-man (Fig. 7.9) or double-incline trunk shaking harvesters (Fig. 7.10) on tart/sour cherry (for processing) systems. The cherries are collected into tanks containing cold water for both cushioning the cherries when dropping into the tanks and to begin field heat removal. These large trunk shakers are also used for harvesting processing-destined sweet cherries. These systems have evolved to be gentler on the tree and the fruit and with trained operators can harvest cherries at a rate in the range of four trees per minute, which can equate to nearly 500 lbs. per minute if conditions are optimal. There is some promising investigation into using canopy shaking for tart cherries and using such for trees in their first 5 years after planting as they are at that time too tender and young for trunk shaking yet are small enough on which to operate over-the-row machinery. This can result in bringing some positive cash flow from the harvest of very young trees, whereas, in the past, it has not existed. Canopy shaking coupled with modifying the growing system of the trees to be more dwarfing or bush-like could lead to canopy shaking throughout the life of the orchard. This latter is an example of developing the machinery in concert with changes in the growing system to arrive at a new and hopefully improved approach that is more sustainable.

7.5.2 Oranges

Canopy shaking has been utilized in oranges for processing harvest with large spindle-tine systems. Depending on the size of trees, the system for larger trees may utilize two machines, having very long and stiff tines, in which each works from one side of the tree and each carries a collection surface and conveyor extending under the tree (see Fig. 7.12). A single over-the-row spindle-tine machine has been used on smaller trees. Like some apple shaking systems, fruit is sometimes shaken to the ground and subsequently retrieved with a sweeping and pickup machine.

Fig. 7.12 Spindle-based canopy shaking concept of orange harvest system. (Photo by Daniel Guyer)

7.5.3 Grapes

With grape production involving long and relatively narrow trellised rows of vines containing fruit, canopy shaking with over-the-row bow-rod or sway-bar harvesters is effective and common (see Fig. 7.6). In grapes, the fruit is destined for processing and will be squeezed/damaged anyways, so aggressive shaking of the bush plus direct contact of the sway bars and rods on fruit clusters works well to remove the fruit with a combination of inertial forces via shaking of the vine plus direct hitting of the clusters by the shaking mechanism and via "abrasion" between plant parts. Because it is set to be quite aggressive, it is non-selective, and a considerable amount of material other than grapes, termed MOG, is collected and must be separated out, which supports that postharvest systems must often be developed in parallel with mechanical harvest/detachment systems. In some vineyards, the vines are tall and quite substantial and have a rather significant woody trunk, and thus some harvesters utilize a form of trunk shaking that can operate continuously as it involves two parallel bars into which the trunks feed and the bars are shaken back and forth parallel to the ground causing the grapes and vines above the stem/trunk to shake back and forth with high frequency and subsequently detaching the fruit. In this system, there is no direct physical contact of the shaking mechanism with the fruit and smaller vines of the plant.

Some advantages of mechanical harvesting in grapes are that studies show a human can harvest about 1–2 tons/day, whereas a machine can harvest 80–200 tons/day. Related, the studies found a harvest cost of \$230/ton for hand-harvest grapes and \$115/ton for machine harvest. Additionally, a faster harvest (from picking to processing) is more desirable for many end products. Manual harvest logistics are such that it requires more time to get an orchard/vineyard completed, and therefore not all the fruit can be harvested at the optimal time, some too early and some too late. Machine harvest also has the advantage of being able to harvest at night, which can extend the harvesting hours, and/or harvest can take place during cooler periods of the day.

Some disadvantages of mechanized grape harvest are humans can be more selective, but it requires training and financial motivation. Excessive leaves and twigs and insects are more likely with mechanical harvest, as is damage to the vine, with the latter providing disease and insect introduction sites. Some grape vineyard topography is such that operating mechanical systems, even self-leveling machines, is not feasible or possible.

7.5.4 Apples

Trunk shaking combined with either a catching frame underneath or shaking to the ground and subsequently using a separate machine for sweep and pickup are two systems that exist but are uncommon for mechanical harvest of processing apples. The apples are shaken to the ground and swept up with brushes and conveying systems. For most applications, the food safety acts prohibit the use of fruit picked up off the ground due to potential fecal and other contamination. With apples being highly sensitive to bruising, apparent opportunities for mass or semi-mass harvesting seem a large challenge for the fresh market. Most mechanical harvest focus for fresh market apples is on robotic or partial robotic systems that address fruit harvest on fruit-by-fruit basis (see below robotics section). Some study is being conducted on shake-and-catch systems that implement localized shaking and catching where the shaking of individual limbs occurs, and the growing structure is such that the catching surface can be brought into very close proximity under the branch, and the fruit falls only a short distance onto cushioned surfaces. Several mechanized "harvest-assist" systems are being developed to effectively support human pickers. However, such systems are not discussed here as they do not meet the definition of mechanical-induced detachment.

7.6 Robotics: The Future?

For a system to be considered robotic can have various interpretations. Here the discussion definition will be on systems that do all of detecting/locating, selectively harvesting, and bringing the fruit to a position ready for it to be further handled, essentially mimicking the human picker, although possibly doing so in a unique way. However, the goal to keep in mind is to harvest at a higher rate than a human (presuming hand labor is available), and as an example, for apples, one worker on an orchard platform can maintain a picking speed of approximately one apple every

1.5 s while actually picking, with an efficiency greater than 95%. Thus, replacing ten pickers with one machine would require building a robotic harvester that is ten times faster and picks gently enough to harvest 95% of the fruit successfully without damage and do so at a cost less than the wage of ten human pickers (Vougioukas, 2019).

The breakdown of all the intelligent and skilled tasks a human picker conducts in the process of harvesting an individual fruit is quite amazing. These include identification, maturity/readiness determination, location, positioning, traversing through obstacles, grasping and applying proper harvest motion and force(s), carefully collecting, and transporting to a collection point. Components/concepts are mostly separately being studied with some success to electronically/mechanically complete such tasks. However, putting it all together into one system adds significant complexity. Often developments of such individual operations are trying to duplicate the human action, whereas it is also important to "think outside the box" and potentially complete the tasks in a completely unique way; and again, this is likely to mean a systems approach that involves unique electronic/mechanical tooling and systems along with an adaptation of the growing system.

Robotics or "automatic" harvesting must try and mimic all of these very articulate and advanced human sensing, decision, and physical operations *OR* the overall system must be changed to remove or simplify the need for a given subtask. One advancement that appears to no longer be a limiting factor is the computing power/capacity/ability to process, in real time, the massive amount of data gathered and needed in making automated intelligent decisions.

7.6.1 Robotic Subtasks

Based on the chapter definition of a robotic system above, for discussion presentation purposes, a robotic system can be broken down into three "macro" aspects/tasks: (1) identification of fruit and its location, (2) movement to the individual fruit location and detachment, and (3) controlling the detached fruit and moving it to the subsequent handling system.

7.6.1.1 Identification of Fruit and Its Location

It is reported (Bachche, 2015) that the visibility of fruit in conventional plantings is on the order of 40–50%, whereas the fruit visibility in more dwarfing/hedge/fruiting wall systems can be 75–80%; and this is increasing with highly managed fruiting walls on trellises. This combination of simplification of the environment and advances in optical components/hardware and high-power computing has helped advance the automated identification needed for robotic harvesting. Identification systems generally involve a high-resolution digital camera and image processing and pattern recognition algorithms that can detect the target (fruit) using either color or shape recognition and usually a combination of these. Many studies exist to detect fruit on trees, with occlusion and clustering being two large challenges for identification for mechanical harvest. These are challenges that can be reduced with certain growing systems. The two automated visual approaches are to use continuous imaging located on the end of the robotic positioning arm/device and continually updating and guiding as the robot moves toward the fruit (sometimes termed closed-loop) and to use cameras onboard the base unit that image the scene, and subsequently, the location of the fruit is determined via the geometry of the camera positions, often termed binocular vision. This is also termed open-loop. Another possible approach is 2-D imaging coupled with some other sensing such as laser range finding. Any degree of freedom which can be eliminated in getting to the fruit position greatly improves the success and practicality of mechanical harvest. Electronic/automated fruit identification on the tree and subsequent motion articulation, while a component of robotic mechanical harvest, significantly overlap with fruit detection and other electronic tree assessments discussed to more extent in Chaps. 2 and 6.

7.6.1.2 Movement to Fruit Location and Detachment

Many exciting research efforts have been, and are being, undertaken in this interesting sub-domain of mechanical harvesting. It is widely recognized that purely simulating human intelligent and articulate movements within conventional growing systems is not a feasible approach; however, there have been attempts. More promising robotic approaches are associated with growing systems that reduce variables and simplify the scene and task. Prototype robotic systems have included hydraulic, pneumatic, and electrical-based operation for the movement to the fruit location and for operation of the end-effector in grasping and/or detaching the fruit. Some of the basic concepts attempted have been encompassing or grasping an individual fruit, or coming up under it with a small individual catching system, and including a concept/means of knifing or scissoring of the stem as part of the overall end-effector. A second basic concept is to implement actual actuated grasping fingers, and most recently looking at the potential of soft robotics, and then conduct a picking motion similar to the tilt or twist motion of a human picker to detach the fruit. Navas et al. (2021) review some soft robotic efforts in the agricultural domain. Another concept is to implement linearly actuated arms that can move to the fruit, and the end-effector uses suction to grasp the fruit, and then either the end-effector or the entire arm twists and retracts to perform a detachment function. The work by Zhang et al. (2021) is an example of such. This latter system has the advantage of possibly being gentler on the fruit and only needing to see and address one side of the fruit without needing precision 3-D positioning information. The challenges for all of these systems are they must be rugged yet gentle, have high speed, and have the ability to adapt to varying shapes and, in many cases, adapt to interferences from branches and/or other fruit. Kootstra et al. (2021) and Zhou et al. (2021) present some recent reviews and synthesis of specialty crop robotic harvest systems and concepts and challenges.

7.6.1.3 Controlling the Detached Fruit and Moving It to the Subsequent Handling System

For a robotic-type concept to be fully successful, the fruit needs to be transported from its position on the plant to the collection bin and do so rapidly or without overall harvesting delay as well as without damaging the fruit. This can be as challenging as the above location and detachment steps. One concept involves the obvious retraction of the picking "arm" back to a collection point with each fruit harvested and the release of the fruit into a bin or conveyor, which requires significant travel time in which the robot is not in the action of "harvesting." Another concept is the use of vacuum through large-diameter padding-lined tubing, which is similarly used in human picking harvesting aid platforms, such as the DBR system (see Fig. 7.13) to allow the human picker to be more efficient and focused on the highly skilled task(s). In these concepts, the challenge is minimizing any bruising damage.

Examples of "robotic" systems are the robot by Abundant Robotics, which is shown in Fig. 7.14, and the FFRobotics system shown in Fig. 7.15. These systems are fully robotic and use vacuum for the detachment and, in one case, also for conveyance but require a rather highly structured nearly 2-D planer fruiting wall growing system. It is of note that such growing concepts are demonstrating positive horticultural results regardless of importance to mechanical harvest. These emerging systems are reporting a harvester replacing 20–25 human pickers per day, and 1 harvester could cover approximately 125 acres in a season.

Significant study can be found historically and presently for each of these subtasks, with putting them all together into a functioning system being less prevalent. However, those which are based on the least complex concepts are seeing emergence at the potential commercial application level.

Fig. 7.13 Vacuum conveyance by DBR conveyance concepts. (Photo by Daniel Guyer)

Fig. 7.14 Robotic harvest development by Abundant Robotics

Fig. 7.15 Robotic harvest development by FFRobotics

7.7 Summary

The challenge in mass or semi-mass mechanical harvest is generating the optimal force(s) to detach the fruit and, in doing so, limit damage to the tree/vine and carefully catching the commodity. While challenging, this is achievable in controlled and consistent growing systems but is exponentially difficult in highly variable biological environments. Robotic systems are emerging with the coupling of the simplest mechanical concepts with plant systems which reduce variability and challenges showing the most promise over those attempting to mimic human pickers in conventional fruit plant systems.

As noted throughout this chapter, many of the concepts are possible and have been demonstrated in lab conditions and/or ideal field conditions. However, the added challenge of biological variability has prevented a no-fail solution and, subsequently, full-scale commercialization. Nevertheless, the sense is we are at or very near the "breakeven" or "crossover" point for mechanical harvest in many more commodities and sizes of producers based on advancements in technology and computing and the costs associated with such vs. labor availability and cost. Merging, compromising, and compatibility of tree/plant design and machine design concepts is critical and essential.

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Chapter 8
Autonomous Platforms

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Abstract In this chapter, we discuss how robotics is used in precision agriculture for orchards and vineyards to automate and simplify tasks. We focus on the aspects required for a system to function autonomously and less on the actual task. Topics include ways in which platforms track their positions, such as GPS; what types of sensors are generally used on top of location; and how this data is used for decision-making and human safety within the navigation and mobility concept. We also discuss other high-level topics, such as path planning and optimization and fleet management, to explain the necessary aspects that play behind the scenes. Lastly, we present an overview of existing commercial and emerging technologies for applications in orchards and vineyards.

8.1 Introduction

As more and more sensing, perception, and actuation applications emerge in the fields discussed in previous chapters, it is becoming more difficult to consider every aspect manually. The increasing workload is intensified by the labor shortage within several sectors (Taylor et al., 2012; Rye & Scott, 2017), as well as the increasing demand to feed the growing population. To implement new technologies, farmers, therefore, need to rely on autonomous platforms to carry out the tasks. We define an autonomous platform in an agricultural setting as a robot that carries out operations without manual intervention, often used to automate repetitive, hazardous, and/or easy operations to make the agricultural task more convenient for the human being. Carrying out operations without manual intervention requires the system to meet two basic autonomy principles: autonomous navigation and autonomous manipulation. This chapter will discuss the aspects of the first in more detail, as the latter requires this platform when striving for full autonomy.

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For autonomous navigation to be possible, the system needs to be aware of its surroundings in several ways. Firstly, knowledge of the platform's location is crucial for the overall task, such that the platform can make decisions based on its position. Secondly, being able to perceive the local environment is also of great importance to avoid obstacles such as trees or vines, other obstacles, and people. Additionally, the system will need to be able to make decisions based on the perceived environment, such as reducing or eliminating the need for manual intervention.

In short, although it is possible to know and document the exact planting location of the trees and vines with high precision and low uncertainty, plants grow naturally. An autonomous system will therefore need to base its actions on the actual state of its surroundings to avoid obstacles such as branches and reduce the potential damage to plants, crops, and the robot itself.

This chapter starts with a section on sensing, which explains the systems needed for positioning purposes and other sensing capabilities found in agricultural robots. Section 8.3 discusses the decision-making algorithms and how data processing is carried out. Section 8.4 is dedicated to planning and optimization architectures, which guide robotic platforms on a higher level. A brief discussion of the implementation actuators and their control systems is presented in Sect. 8.5, followed by an overview of necessities for fleet operation in Sect. 8.6. Section 8.7 presents some other solutions as well as examples of existing commercial and emerging technologies. Finally, concluding remarks are covered in Sect. 8.8.

8.2 Sensing

Agricultural autonomous platforms are designed to move themselves and the attached equipment to certain positions to carry out tasks. This means these systems will need to know their exact position and understand their environment before being able to make decisions. This section discusses the different sensing techniques used within autonomous platforms and is structured to discuss course sensing first and precision sensing last.

8.2.1 Absolute Positioning

To position themselves, autonomous platforms generally comprise a geospatial positioning system, often consisting of a global navigation satellite system (GNSS) receiver to make sense of GPS, Galileo, or other satellite positioning data. GNSS work by triangulating the distances measured from multiple satellite sources. Unfortunately, regular GNSS data only allows for positioning accuracy of about 2–4 m, which can be sufficient for (autonomous) cars on a fixed road network. Still, depending on the required application, it often is too large for precision actuation on crops. Distances between vineyard rows can be as small as 50 cm, which requires a higher accuracy to navigate than in orchards with larger spaces between the trees.

To overcome this shortcoming, some studies increase accuracy using object detection and local sensing methods (García-Pérez et al., 2008). These methods are discussed in Sects. 8.2.2 and 8.2.3.

A more generalized approach to improve accuracy is to use GNSS augmentation. Satellite-Based Augmentation Systems (SBAS), like Europe's EGNOS technology, or Ground-Based Augmentation Systems (GBAS), like Differential GPS (DGPS), can typically increase positioning accuracies to errors smaller than 1 m and in favorable conditions up to 2–5 cm. An example of such a technology is Real-Time Kinematic (RTK) positioning, widely applied in many commercial applications. This method falls under Observation Space Representation (OSR) technologies and relies on the user to send its approximate location to a processing station, which compares the measurement with those from base stations with known positions and sends a corrected position back to the user. Studies like Garrido et al. (2015, 2019) and Bengochea-Guevara et al. (2018) rely on this technology to accurately measure positioning. Nevertheless, this approach needs to be close to a base station (typically within 30–40 km) to assure high accuracy and needs two-way communication.

Specific approaches aim to lower the necessity for two-way communication and proximity to base stations by using State Space Representation (SSR) methods (Wabbena et al., 2005; Wang et al., 2018). SSR also uses base stations but uses their measurements to model the disturbances over an entire area and sends this correction model to the user.

Another way to improve accuracy is dead reckoning. This approach aims to compute a current location using a previously known location (and orientation) and increment it with known or estimated speeds over the elapsed time. The term odometry is also often used, which describes using motion sensors to estimate a change of position over time. A widely applied sensor is the inertial measurement unit (IMU), a composite sensor that comprises accelerometers, gyroscopes, and sometimes magnetometers (or compasses). Moreover, typically, an IMU has one of each sensor per axis of the vehicle to measure changes in any direction. Other solutions use encoder data obtained from the wheels or separate accelerometers, gyroscopes, and compasses. Studies such as Lan et al. (2019) aim to use the data from these sensors to improve accuracy or reduce the required amount of GNSS data necessary. Note that when using dead reckoning, errors increase over time, and hence, regular inputs of reliable positioning data are necessary to maintain an accurate position over time. Nevertheless, also, in this case, other local sensing methods could be introduced to keep the errors low and reliable (Yang et al., 2020).

8.2.2 Relative Positioning

Another common issue with GNSS signals is that the canopy of the orchard or vineyard and other surfaces (e.g., agricultural vehicles themselves) reflect them and thereby induce extra uncertainty to the measurements (Valbuena et al. 2010). Even though odometry/dead reckoning is one available solution to overcome this by augmenting the available signals, another way is to position oneself relatively to the plants. Relative positioning is defined as the placement of the vehicle with respect to other objects. In the case of agriculture, objects may refer to crops, plants, or the produce but also the ground and human beacons placed for local positioning purposes such as (colored) poles or tags. Studies like Aqel et al. (2016) and Zaman et al. (2019) discuss visual odometry, which mainly focuses on tracking the robot's motion by using camera images. Other studies focus on object detection to deduce location directly (Azevedo et al., 2019).

Furthermore, relative positioning is also used for a broader application, namely, object detection and avoidance (García-Pérez et al., 2005; Vasconez et al., 2019), but also that of object recognition for precision application purposes (Burgos-Artizzu et al., 2011; Gonzalez-de-Santos et al., 2017). The first has a goal to assess risks and take actions to minimize them, not only for the autonomous platform itself but also for the human operators and the crops. The goal of the latter use would be to perform the necessary action in a precise location, for example, fruit picking, which requires the robot to see where the fruit is with respect to its equipment, or a weeding robot that only applies herbicide on the weeds. The sensors used for these applications are discussed in Sect. 8.2.3, whereas the processing thereof and decision-making are discussed in Sect. 8.3.

8.2.3 Onboard Sensors

As explained in the previous section, autonomous platforms need different types of information to make good decisions. There are many types of sensors available and built into commercial equipment. We will mainly discuss noninvasive sensing techniques, as many invasive ones (like soil and crop sampling) require relatively long processing times and are therefore not suitable for making real-time decisions. The first sensor we will discuss is perhaps the easiest to imagine; however, it is not as easy to implement.

8.2.3.1 Cameras

Briefly summarized, a camera is a device that captures (in our case, visible) light through a lens set and projects it on a photosensitive sensor that captures the intensity values of certain wavelengths. The most common camera is the RGB (red, green, blue) camera, which can be found in most smartphones, but also the larger reflex cameras belong to this type. They are a good way to feed a system with the information that we humans are used to obtaining with our eyes. However, until recently, it was computationally very expensive to process this data into useful information. Current machine and deep learning techniques give us a digital way of mimicking brain-learning functions, thus making it possible to make images understandable to robots.

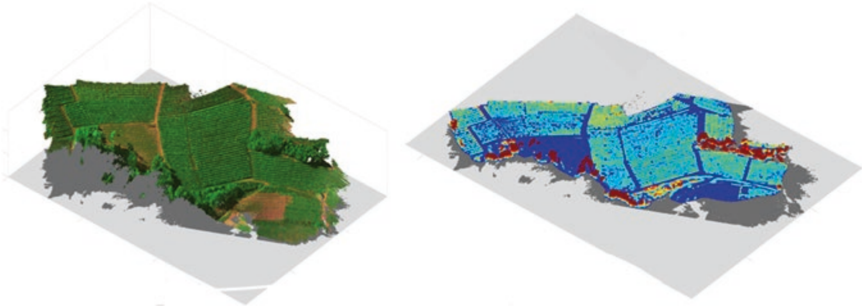

Fig. 8.1 3D reconstruction of a vineyard (left) and adapted view of the data (right). (From Comba et al., 2018)

Studies such as the ones by Gottschalk et al. (2008) and Burgos-Artizzu et al. (2011) propose real-time image processing techniques, and others (e.g., Howarth et al., 2010; Morellos et al., 2016) propose machine learning techniques to identify mature crops and soil composition, respectively.

An interesting possibility is that of 3D reconstruction using photogrammetry. When taking multiple pictures from different perspectives, depth information can be extracted and used to the advantage of our system. Using the changing perspective of a system in motion can provide the necessary depth of information. Studies such as Westoby et al. (2012) and Comba et al. (2018) propose exactly this type of technology (see Fig. 8.1).

8.2.3.2 LiDAR and Other 3D Imaging Techniques

LiDAR, or Light Detection and Ranging sensors, function similarly to radar and measure the distance to any object within the range of its light source. Instead of radio waves, LiDAR functions by emitting a light of a certain wavelength in a specific direction and measuring the time of the signal to come back. By doing so in many directions sequentially, it maps its environment by creating a so-called point cloud that can then be converted to 3D reconstructions of the environment of the autonomous platform. This type of sensing is more robust for outdoor uses because it carries its light source but can be more costly to operate.

LiDAR data (as depicted in Fig. 8.2) can be useful for a variety of applications, from phenotyping (French et al., 2016) to regular 3D reconstruction of the plants (Garrido et al., 2015) or combinations thereof (Sankey et al., 2017).

While LiDAR remains one of the most widely used sensing technologies for 3D imaging, there are other options, as explained in Vázquez-Arellano et al. (2016). One interesting sensor is the Microsoft Kinect v2 sensor, used extensively in scientific research such as Bengochea-Guevara et al. (2018) to reconstruct vineyard rows or Rosell-Polo et al. (2017) for a more generalized approach. The Kinect v2 sensor is the second-generation sensor initially designed for the Microsoft Xbox gaming

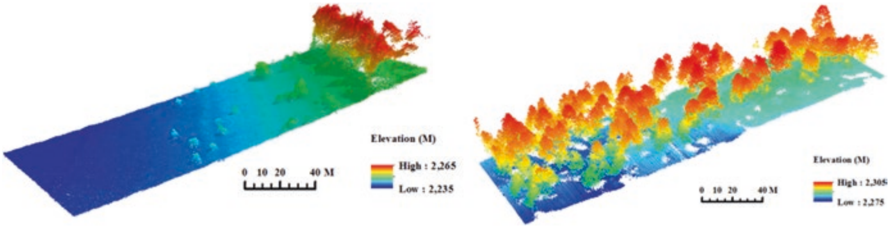

Fig. 8.2 Example of LiDAR point clouds. (From Sankey et al., 2017)

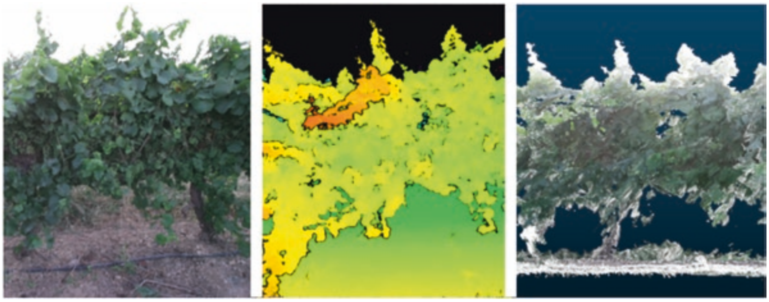

Fig. 8.3 Example of 3D reconstruction of vineyard row using data from Kinect v2 sensor. Left, RGB image; middle, depth information; right, 3D reconstruction. (From Bengochea-Guevara et al., 2018)

system, which uses an infrared laser projector to project a pseudo-random pattern of dots. An infrared camera is placed near the projector. The sensor uses triangulation for each dot between the expected position and the perceived position to infer the distances of the objects in the projected field of view. This typically results in renderings like the one depicted in Fig. 8.3.

8.2.3.3 Hyperspectral and Infrared Imaging

Hyperspectral sensing may refer to collecting information within the electromagnetic spectrum but outside the visible light range. In general, they can be seen as specialized cameras containing a sensor that is sensitive to wavelengths outside the visible spectrum. As discussed in Hartel et al. (2015), current applications range from quality and safety inspections for foods and produce to plant quality evaluations, such as phenotyping (Sankey et al., 2017) or nitrogen mapping within the plants (Yu et al., 2014). The latter application might greatly influence the choices a system makes as to where in a field it will need to go next.

Infrared sensing, effectively a subcategory of hyperspectral sensing, has important usage within agriculture on its own, as it can be used to detect live vegetation using the Normalized Difference Vegetation Index (NDVI). This brings possibilities to distinguish the plant from the soil faster and easier, which can be used to avoid obstacles, as explained by Hamuda et al. (2016). Future applications might be able to use the infrared spectrum to detect humans and improve safety measures, as shown in Aspiras et al. (2018).

8.2.3.4 Other Sensing Techniques

Other sensing techniques exist, but many of them are not as popular or have less potential than those discussed before. This section discusses these technologies and applications, which are less common but interesting.

IMU

Although an inertial measurement unit (IMU) is a sensor most generally used for odometry and dead reckoning purposes (as explained in Sect. 8.2.1), this section briefly discusses other potential uses for IMUs. An IMU consists of accelerometers, gyroscopes, and, optionally, magnetometers to measure orientation changes. It can be used to reduce the uncertainty of the current position by using linear acceleration and rotational rate measurements to estimate the change in position since the last known location.

Besides its primary use, an IMU may also be used to detect obstacles, as it will detect a crash or slipping of the wheels if the vehicle is stuck somewhere (Cismas et al., 2017; Xiong et al., 2019). It could also indicate rough terrain and, therefore, can be used to inspect certain areas that might have changed due to animal activity.

Ultrasound

Ultrasound is sound with a higher frequency than the upper audible limit of human hearing. Although ultrasound is a powerful tool within agriculture in the battle against bacteria and other microorganisms (Gordon, 1963), ultrasonic proximity sensors have been employed in many robotic applications. They are finding their way into agricultural platforms (Tang et al., 2011). This process is called echolocation and uses the same concept as radars and LiDARs to infer the position of objects by using the time difference between the sent signal and the perception of its echo.

Physical Sensors

Although most studies aim for noninvasive sensing techniques, physical switches and buttons are often implemented as failsafe. Such sensors are often used as proximity sensors to make sure undetected obstacles are detected, albeit later than regular operation would require, or as safety switches intended to guarantee the safety of the operators.

8.3 Decision-Making and Data Processing

After collecting a multitude of different sensor measurements, an autonomous platform will need to make decisions based on this information. This section highlights the two main decision categories an autonomous platform must take, namely, decisions relating to safety and task planning. This is followed by a section on how data may be processed to be able to make these decisions.

8.3.1 Decision-Making

8.3.1.1 Safety

Safety-related decisions are those decisions made whenever risks for damage are mitigated. Possible danger to humans and the robot itself and/or the crops fall in this category. When a robot crosses path with a human, an example would be to halt dangerous movements or slow down or interrupt other movements.

As Vasconez et al. (2019) stated, most human-robot accidents are caused by human errors. Therefore, a big factor in reducing the number and severity of accidents is eliminating and mitigating the risks involved in human-robot interactions (HRIs). For safety, it is important that safety signals and the decisions derived from them can overrule the task planning decisions. Studies such as García-Pérez et al. (2005), Cherubini et al. (2016), and Pereira and Althoff (2018) propose predicting and adapting to potential risks to mitigate possibly dangerous situations.

8.3.1.2 Task Planning

Task planning decisions are made when considering the best approach to carry out a specific task. Decisions on how to avoid fixed obstacles and path planning algorithms fall into this category. Also, approaches combining multiple sensor inputs to reduce errors, as done in García-Pérez et al. (2008), belong here.

Task planning decision-making is important such that the use of energy and resources can be optimized. For example, a weed detecting algorithm with many false positives will be carrying out the weeding on places that do not require treatment, and route planning moving around a small stone might use more energy than driving over it. These parameters need rigorous tuning for robotics to be feasible within agriculture.

Task planning can be divided into multiple categories, where overall planning is discussed in more detail in Sect. 8.4, whereas fleet coordination and planning are explained in Sect. 8.6. The remaining planning tasks can be carried out locally and consist of the movement of the autonomous platform to place the application device in the right spot for treatment. Those can range from end-effector or gripper placement, an important task for applications that require flexibility, such as trimming (Kaljaca et al., 2019) or harvesting (Bac et al., 2014), to vehicle motion for applications such as spraying (Conesa-Muñoz et al., 2016c) or monitoring (GRAPE, 2020).

8.3.2 Data Processing

To make good decisions, the data needs to be interpreted. This also means that irrelevant data is discarded and the relevant information understood. A good example is the data from depth sensors such as LiDARs.

Depending on the application, it is not necessary to know the exact shape of the objects in the direct vicinity of the platform. Still, an approximate shape and a location would be enough. This type of data refinement typically results in lower data density but a higher information value.

An example of data refinement is carried out in Digumarti et al. (2018), in which a model is proposed to segment the data into branches and leaves. This can then be used for decision-making, plant monitoring, and/or obstacle avoidance.

In many cases, the information derived from the sensors is stored in databases for future reference. Saving this information with respect to the location in the field and subsequently superposing it on a map of the field is an intuitive way of visualizing it. Studies such as Comba et al. (2018) and Jiang et al. (2019) produce maps similar to those shown in Fig. 8.1. Besides being intuitive for the user to understand and see the field's current status, having this information available per location makes it possible to make local decisions. An autonomous vehicle can potentially base its decision not only on what is perceived currently but also on the history of sensor and actuation information. An example would be sensing a plant needs fertilizer but refraining from giving it because it got a dose the previous time.

8.4 Control Systems

Control systems are the techniques used to manage and regulate the behavior of a device. In essence, robotics is applied control systems. Widely used control setups are closed-loop systems. These systems use inputs from sensors; compare the values against some reference or planned signal, which results in a current error; and aim to reduce said error by the design of the controller.

Many platforms already consist of some low-level control interfaces for some electrical components, such as engine, powertrain, or brake control modules. Therefore, most autonomous vehicles consist of a central computing unit, which makes high-level decisions and gives a more abstract command to the interface of the specific components. Instead of measuring deceleration and using feedback control to adapt the force on each of the vehicle's brakes, the system can just decide to break, and the brake control module will take care of the rest. This does not mean that we do not need any feedback control. On the contrary, most central processing units will be full of it.

Another commonly used approach for the control of autonomous systems is fuzzy control. This field of study is widely used in systems that mimic human behavior, which often cannot be described in a purely binary form. For example, a vehicle's steering, braking, and accelerating are typically not performed in a binary or discrete way (either not braking or fully braking) but in a more analog way (breaking a little or breaking more). The concepts of fuzzy logic make it possible to control vehicles in such a way and make the programming logic more understandable for humans. Applications vary from generic autonomous navigation (Mohammadzadeh & Taghavifar, 2020) to specific agricultural tasks (Bengochea-Guevara et al., 2016). Other studies aim to reduce the error of the navigation control systems by using extra information ranging from low-cost IMUs (Si et al., 2019) to the use of visual odometry (Zaman et al., 2019).

8.5 Path Planning and Optimization Systems

Although many aspects can and should be computed in real time to allow for the proper functioning of the robotic systems, others cannot. These encompass planning and optimization systems, as these typically include (NP-Hard) problems that cannot be solved in relatively short times.

Although it might look easy at first, route planning becomes more difficult once more variables are considered. Examples of extra variables are the number of vehicles, the size of each vehicle's fuel tank or battery, the location of the refueling or charging point, and the turning radius of each vehicle. All of those affect the result of an optimal path. Research such as Conesa-Muñoz et al. (2016b) and Conesa-Muñoz et al. (2016a) propose ways to improve current algorithms and take these variables into account (Fig. 8.4).

In some orchards, when there is enough space and no irrigation infrastructure between trees in a row, optimization could be taken a step further because it is

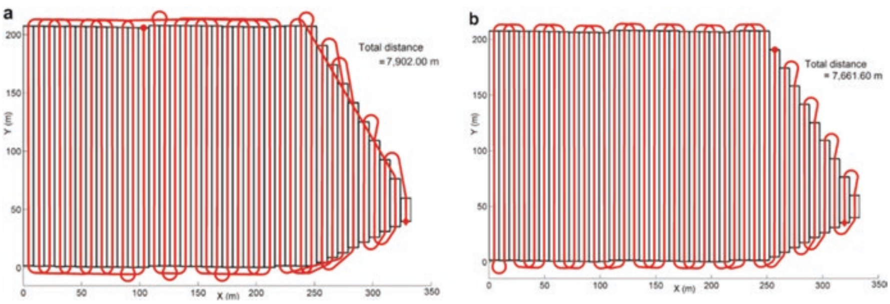

Fig. 8.4 Example of results of two path planning optimization algorithms, with total distances of 7902 m (**a**) and 7661.6 m (**b**). (From Conesa-Muñoz et al., 2016a)

possible to change the paths vehicles take within the field, as they can maneuver between the trees. In contrast, in typical vineyards, this is impossible, as they are arranged in fixed lines. This can especially be interesting if treatment is not necessary in all regions, which can be the case when treating weeds.

Another emerging optimization field is water use optimization, as carried out by Zhang and Guo (2016), aiming to reduce total water use.

8.6 Fleets

As briefly mentioned before within the path optimization section, systems comprising multiple platforms exist and are becoming more prominent in several studies (e.g., Conesa-Muñoz et al., 2016a, b, c; Gonzalez-de-Santos et al., 2017). Fleets of robotic systems are beneficial as they can induce a reduction in vehicle size but also an increase in efficiency and redundancy. As such, they can reduce soil compression and downtimes. Fleet management strategies can be divided into two main categories, namely, centralized and decentralized decision-making, both of which have pros and cons, as discussed in De Ryck et al. (2020). Both will be explained in more detail below.

8.6.1 Centralized Fleet Management

Centralized fleet management refers to a fleet of multiple robots managed from one (external) location, which we will call "the manager." The platforms will need (semi-)continuous communication with the manager to share the collected knowledge and obtain new tasks. The manager, in this case, has an overview of the entire operation and can make decisions accordingly. For example, when one vehicle encounters an area needing a certain treatment, the correct vehicle can be sent there using an optimal route and making sure none of the vehicles collide in the act.

The advantages of these systems are that one entity has all the information, which makes it easy to document and log the carried-out tasks. The overview is kept in one place, and it is easier to test and check as everything is in one place. Another advantage of such a system is that it can consider every vehicle to optimize the tasks throughout the entire fleet. As a result of the above, it is easy for the farmer to track the overall progress and have a forecast for the remaining time.

This strategy, however, also has some disadvantages. These mainly lie in the scalability of the system. Increasing the number of vehicles in the fleet will greatly impact the optimization software that generally takes exponentially more time to find an optimal solution with respect to the number of vehicles. Often such strategies will favor optimization algorithms that generate known good solutions instead of optimal ones as a trade-off for the time needed to compute optimal solutions. Another slight disadvantage is that the entire system must be computed again with any unexpected change.

Examples of studies using centralized control are Doering et al. (2014) and Barrientos et al. (2011), in which fleets of aerial vehicles are controlled from a single location and where global optimization is carried out.

8.6.2 Decentralized Fleet Management

Decentralized fleet management refers to the robots within the fleet making decisions on their own based on their perceived environment and the communication with nearby vehicles. These vehicles will, in general, compute and follow suboptimal routes; any loss in efficiency could be compensated by adding more vehicles. In general, it cannot be guaranteed that the paths chosen will not cause longer non-productive paths. The computed solutions will also be more myopic than those computed by centralized management because the future states of the entire system are not yet known. A major advantage of decentralized systems is that they are easily scalable, as none of the nodes of the system requires a high computational load. Also, due to the myopic choices, errors and unexpected changes are mitigated easily and do not affect the system as much. Disadvantages include the lack of central knowledge and, therefore, easy forecasting and tracking methods. However, this can be improved by communicating with a central dispatcher, which enables documenting, logging the carried-out tasks, and generating the desired overview. Examples of studies in decentralized control mainly focus on the flexibility of the controller's scalability (Ju & Son, 2018) and the flexibility of the vehicle behavior (Franchi et al., 2011).

8.7 Examples of Existing Technologies

As part of the SPARKLE Project, co-funded by the Erasmus+ program of the European Union, an analysis has been carried out of the state-of-the-art robotics within the field of precision agriculture. Part of this analysis showcases existing commercial and emerging technologies, of which the most relevant ones within orchard and vineyard treatment are outlined in this section, which is expanded with other research projects and prototypes.

VITIROVER

As a part of weeds management, Vitirover Solutions (2020) proposes to use fleets of robotic lawnmowers to prevent weeds from growing in the first place. Their small, lightweight robot is meant to mow the grass in between the rows of trees or plants, thus reducing the use of herbicides and glyphosate in particular. As shown in Fig. 8.5, it is equipped with a solar panel to extend its working range. It is also equipped with GPS to navigate predefined areas and is monitored remotely by a technician. This robot is highly independent, as it does not require any human

Fig. 8.5 VITIROVER robotic mower fleets can be used to manage grass. This is used to reduce weeds in both orchards (left) and a vineyard (right)

interactions. The important decisions are made remotely by a human operator, which indicates the use of a centralized control strategy.

Autonomous Orchard Sprayer

The automatic orchard sprayer GUSS (GUSSAG, 2019), shown in Fig. 8.6, is specifically designed to reduce health threats to operators who would otherwise carry out the driving. Furthermore, it allows for fleet operation from a single control location. This type of robot uses a wide variety of sensors to guide it along a precise route while being safe for its environment.

Naïo TED

An interesting example of mechanical weeding is TED (Naïo Technologies, 2020). This robot, shown in Fig. 8.7, and clearly designed for vineyards, can carry various tools for different applications. The main task this robot was designed for is weeding, but prototype tools exist for various other tasks such as blossom thinning, trimming, and spraying.

This tool is still experimental to some extent but has a lot of potential due to the possibility of testing new applications while already being of use to farmers. It navigates using RTK GPS and follows a map created using drones beforehand. Although this does not directly count as a fleet, it has the potential to augment and share data from multiple sources, and future heterogeneous fleet implementation is foreseeable.

Vision Robotics Grapevine Pruner

This pruning solution from Botterill et al. (2017) and Vision Robotics Corporation (2019) is currently only a prototype and is awaiting financing to be fully developed. Although the technology mainly focuses on actuation instead of navigation, the finished platform aims to be fully autonomous.

The interesting part of this system is the implementation of artificial perception, as shown in Fig. 8.8, to understand the system's environment as a regular human would. A finished system could incorporate many other visual cues to understand other aspects, possibly contributing to the vehicle's autonomy.

Fig. 8.6 GUSS autonomous orchard mist sprayer

Fig. 8.7 Naïo TED, a mechanical vineyard weeder

Fig. 8.8 Vision Robotics Grapevine Pruning system towed behind an autonomous tractor (left) and the artificial perception of branches (right)

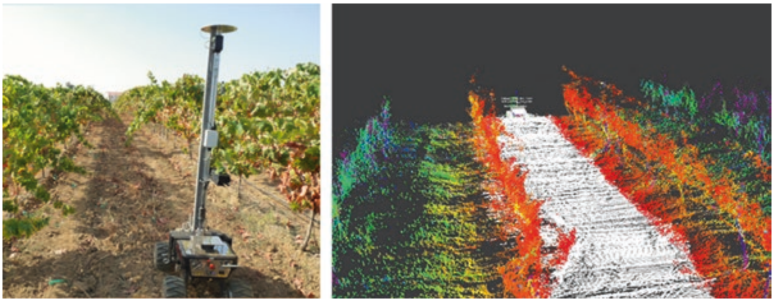

Fig. 8.9 VINBOT vineyard monitoring platform (left) and its 3D interpretation of its environment (right)

VINBOT

The following system is not a commercial product either and has been developed by a consortium within the European Union and is especially interesting for its autonomy. VINBOT (2019) is designed as a monitoring vehicle to map and measure critical aspects of the vines.

As shown in Fig. 8.9, the mapping capabilities seem promising, and the specified capabilities include monitoring of water and heat stress, canopy density and color, diseases and nutrient deficiencies, and yield estimations (Lopes et al., 2016).

VineScout

Similar to the previous system (Saiz-Rubio et al., 2018; VineScout, 2020), VineScout was developed within a project of the European Union (H2020) to monitor and improve yields within vineyards. Figure 8.10 shows the autonomous ground robot, which has been designed, built, and demonstrated in commercial vineyards. The VineScout goal is to provide massive data such that artificial intelligence techniques based on big data may be applied to build solid models. These models are expected to assist farmers in decision-making about irrigation and harvesting logistics.

Other interesting solutions funded by the European Union are:

1. Swarm Robotics SAGA (SAGA, 2020), part of the European ECHORD++ program that aims to develop fleets of aerial vehicles to monitor and map the environment using a decentralized control strategy.
2. TrimBot, supported by the Horizon 2020 program (Hemming et al., 2018), (TrimBot, 2020), focuses on producing a flexible plant trimming and cutting robot. It consists of a small autonomous platform and a robotic arm, which holds a cutting tool at the end. Because of the robotic arm configuration, the system is not tied to fixed cutting and trimming patterns but instead can base the decisions on each plant.
3. GRAPE (GRAPE, 2020), another European ECHORD++ project, aims to make a small autonomous robot for vineyard monitoring and protection and a small robotic platform with a robotic arm to perform specific tasks in certain locations.

Fig. 8.10 VineScout vineyard monitoring platform

4. RHEA (Gonzalez-de-Santos et al., 2017), supported by the 7th Framework program, is a fleet of small, heterogeneous robots – ground and aerial – equipped with advanced sensors, enhanced end-effectors, and improved decision control algorithms, which aims at diminishing the use of agricultural chemical inputs, improving crop quality and health and safety for humans, and reducing production costs. RHEA can be considered a cooperative robotic system.

8.8 Concluding Remarks

While current autonomous platforms are in constant development, many agricultural tasks are starting to reap the benefits from implementing them in practice. Even though most of these platforms are not yet fully industrialized, prototypes and rudimentary versions are being tested and show promising results. Autonomous platforms are especially useful to tackle the problems arising with the decreasing number of both skilled and unskilled workers while at the same time allowing the vehicle to stay small to combat soil compaction issues.

Expectations are high when considering the possibilities to combat current ecological challenges such as global warming and the biodiversity issues in agricultural regions. Autonomous platforms will become increasingly important as trust and knowledge increase, and a couple of specific areas are expected to reap the benefits autonomy brings.

Firstly, even though autonomous tractors are being developed, autonomy can have a larger impact on other areas of agriculture. One important area is the use of fleets, where autonomy serves as a catalyst. Without it, herds of smaller vehicles would not be sustainable nor economically sensible. It is expected that the market for fleets will make its debut in the coming decade and will grow further in the next.

Another area in which autonomy can be of great importance is within the implements. While navigational autonomy is not yet fully functional, implements can already reap its benefits. Smart implements would only rely on a driver and will be able to carry out the tasks without further human intervention. This intermediate step can greatly increase acceptance as well as the adoption rate.

Lastly, drones, or unmanned aerial vehicles, are expected to increase autonomy and open an important new market opportunity, namely, data analytics. This field is expected to be of huge importance for developing new technologies, as choices farmers typically make using experience can be understood and aided from a data-driven perspective.

Acknowledgments This chapter is partly based on a technological overview written as part of the SPARKLE Project (Erasmus+ program) and the FlexiGroBots project (Grant agreement ID: 101017111), both EU funds. An analysis has been carried out of state-of-the-art robotics within precision agriculture.

Disclaimer The examples mentioned in this chapter are a portion of the existing technologies aimed to represent the current capabilities with respect to autonomous navigation. The companies or organizations behind these examples have contributed to the analysis other than the information provided in publications. Their mention does not imply endorsement by the authors, nor does absence imply discrimination.

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Chapter 9
Management Information Systems and Emerging Technologies

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Abstract The following chapter addresses the principles of farm management information systems, i.e., computational, communication, and algorithmic subsystems, that integrate sensing, actuation, data management and analysis, knowledge of horticultural practices, and decision-making to automate the operation and management of modern orchards and vineyards. Topics include types of data and information, infrastructures, architectures, standardization, data ownership and sharing, and decision support system technologies.

9.1 Introduction

9.1.1 Farm Management Information Systems for Crop Production

During the last few years, rapid technological developments have introduced radical changes in the working environment in the agricultural sector. The level of complexity for farming enterprises has gradually increased in recent decades. Agriculture has entered a new data-driven era, in which access to accurate and timely information is of vital importance. Simple production units have evolved into agricultural businesses with multifunctional service sectors (Fountas et al., 2015a). Thus, modern farms can survive financially and be sustainable only when well managed (Husemann & Novkovic, 2014). However, farm management is a challenging and time-consuming task (Paraforos et al., 2017), with farm operations and activities often not being properly logged systematically and analytically (Fountas et al., 2015a).

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Farmers need an effective way to manage large volumes of information and technological tools to help them make optimal and sustainable decisions year-round (Paraforos et al., 2016). Farm management information systems (FMISs) are systems that support the collection, processing, and storage of data in a form that allows for the accurate scheduling and execution of farming operations (Fountas et al., 2015a; Sørensen et al., 2010) or provide farmers with valuable information to support decision-making. Figure 9.1 shows a commercial FMIS application for crop production, extensively used in vineyards, called SITI4farmer. ABACO's precision

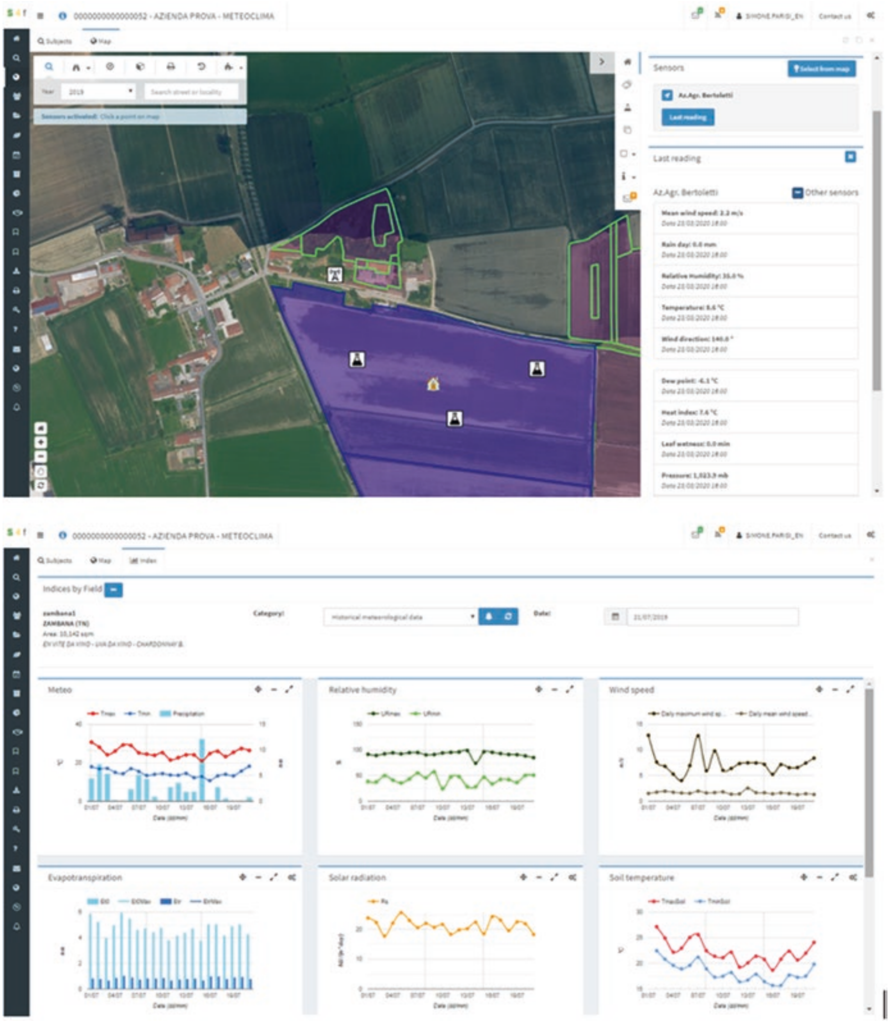

Fig. 9.1 Weather stations' latest readings and historical weather data are stored in the SITI4farmer, ABACO's precision farming tool. SITI4farmer is an example of a crop management platform and a decision support system, widely used in viticulture

farming tool collects sensor-based data, such as weather and soil, satellite data, and other historical data. It provides the user with easy-to-understand visualizations of this information.

Several FMIS structures and software architectures have been presented, while a constantly increasing number of commercial solutions are available on the market, such as 365FarmNet, AgriWebb, Agworld, FarmLogs, and FarmWorks (Ampatzidis et al., 2016; Nikkilä et al., 2010; Paraforos et al., 2017).

9.1.1.1 Historical Overview

The first agricultural FMISs were developed in the 1970s and focused on record-keeping and operations planning. In contrast, more complex record-keeping platforms with integrated decision support tools covering irrigation, pest management, and fertilizer applications appeared during the next decade. It was not until the late 2000s that precision agriculture (PA) as a concept emerged and introduced the consideration of agricultural fields as heterogeneous entities that required selective treatment instead of homogenous entities that are treated equally (Aubert et al., 2012). For this reason, new information systems focused on accurate farming operations were required (Cardín-Pedrosa & Alvarez-López, 2012). For the first time, farmers obtained the ability to generate large amounts of data using sensors and satellite systems (Tozer, 2009). As a result, efficient data management became a top priority, and sophisticated information systems using the newly introduced concept of "field variability" became necessary.

9.1.1.2 FMIS for Precision Agriculture

PA refers to information technologies and electronic communications and the implementation of more accurate Global Positioning Systems (GPS) that enable farmers to collect large amounts of data to use effectively for site-specific crop management (Aubert et al., 2012). Sensor arrays provide constant streams of data on soil properties such as moisture, temperature, humidity, and crop growth parameters information derived mainly from crop spectral reflectance. These data can help understand field variability and allow appropriate management practices to be implemented accordingly (Matese et al., 2009). This has created the need to design and develop dedicated FMISs to cope with the increased amount of data generated by applying PA in field production (Fountas et al., 2015b). Similarly, digital agriculture is a broader term that refers to digital sensor-derived data to support farm management decisions (Keogh & Henry, 2016).

9.1.1.3 FMIS Adoption and Profitability

FMIS development and adoption are strongly related to system profitability, with benefits extending to the value of improved decision-making. However, this is often difficult to quantify, as the benefits of using an FMIS could depend on the user's level of satisfaction. Younger farmers without farming experience can benefit from using an FMIS, which automatically generates documentation data and reduces the required task time while providing better management.

Agricultural management software mainly includes production planning, process integration, performance management, quality and environmental resource management, and sales order and contract management. Moreover, field operations management, best practices and predictions, finance, machinery management, traceability, and quality assurance are additional functions or services that many commercial FMISs offer to farm managers. An analysis of commercial software solutions revealed that current FMISs mostly target everyday farm office tasks related to financial management and reporting, particularly those related to sales, inventory, and field operations management (Fountas et al., 2015a).

9.1.2 Applications for Tree Fruit Orchards and Vineyards

Tree fruit orchard and vineyard products are considered specialty crops of high value since they require a significant amount of labor at various stages. Despite being characterized by high production costs, they have emerged as a fast-growing agribusiness segment. Increasing importance is directed toward detailed traceability systems for the product's origin and especially for the treatments used in production (Tsiropoulos & Fountas, 2015).

Fruit production is a demanding sector where trees have high fertilizer and irrigation needs, which should be carefully planned and applied. Optimal pest management, irrigation scheduling, and harvest timing are strongly related to the final quality of the yield (Tamirat & Pedersen, 2019). Furthermore, the timing of harvest is critical to the quality of the yield. For this reason, selective harvesting based on the ripeness level of the fruit in different zones of the orchard is often used. Finally, during critical periods when farming tasks should be planned and executed with utmost accuracy, farm machinery should constantly operate at optimal rates (Tsiropoulos & Fountas, 2015).

9.1.2.1 Pest Control Information Systems

Pest control and applying plant protection products (PPPs) are one of the most critical factors in crop production due to the severe consequences for human health and the environment from irresponsible practices. Agrochemicals directly impact the quality of yields and the market-selling price of the products. Excessive PPP use financially burdens the farmers and results in high residues of hazardous chemicals on the products that subsequently enter the food chain. FMIS can determine periods when disease outbreaks are more likely to occur and help growers apply the exact amount of PPP needed, avoiding overapplication. These systems can comply with legal regulations and agricultural production standards to ensure food safety and environmental protection (Fountas et al., 2015b). Modern spraying machinery for orchards stores spray data for each spray application to automatically produce the farm calendar that records all plant protection product treatments and provides full product traceability (Berger & Laurent, 2019).

9.1.2.2 Irrigation Management Information Systems

Irrigation is a crucial factor in crop growth and product quality. Despite how simple it may appear, irrigation planning and management is an extremely complicated procedure that requires enormous amounts of real-time data and utmost accuracy and timeliness to achieve optimal results. Soil water content and water availability for the plants depend on several parameters, including soil, climate, and topography. When rainfall is insufficient to meet crop water needs at critical growth stages, water stress can cause major losses in fruit orchards. Several projects, such as USERPA (USability of Environmentally sound and Reliable technologies in Precision Agriculture), propose holistic precision agriculture solutions for tree orchards and vineyards, with the focus being directed on irrigation and harvest management to increase the quality characteristics of fruits by optimizing input use while preserving environmental sustainability.

9.1.2.3 Harvest Management Information Systems

Harvesting is an extremely challenging procedure due to the short time window in which fruit is at optimum ripeness for picking. Fruit harvested prematurely or beyond optimal time can potentially affect how desirable the product is to consumers (Chauvin et al., 2009). Accurate and timely collection of data is driving harvest-related decisions on the farm. A harvest management information system that allows access to real-time harvest data was developed in California, USA, in 2016. This integrated system could automatically generate yield maps that provide farmers with data on the productivity of their farms and allow them to investigate factors related to potential spatial yield variability (Ampatzidis et al., 2016).

9.2 Big Data in the Emerging Technologies

Big Data is a hot research topic that has attracted much attention from the scientific community. Although there is extensive literature on the benefits that can be reaped from the exploitation of Big Data, no consensus exists about what a typical definition of the term is. As for existing definition attempts are concerned, it can be observed that these have focused on a wide spectrum of issues and aspects, ranging from Big Data sources, characteristics, and types to technical requirements and the potential impact of Big Data analysis on the socioeconomic level.

Big Data is generated, intentionally or unintentionally, by interactions and transactions digitally performed in our everyday personal and professional lives and ubiquitous sensor-based devices (George et al., 2014). Continuously increasing capacities of tools and infrastructures for collecting, logging, and transmitting data are the main reasons for data abundance, yet big volumes of produced data along with divergence in data types (i.e., structured, semi-structured, and unstructured data) and the increasing rates of data generation keep pushing demands for storage and process-related affordances (De Mauro et al., 2016; George et al., 2014).

To make sense of this overwhelming amount of data, it is often broken down and characterized into the following dimensions, often referred to as "Vs." The "Vs" of Big Data constitute concise and comprehensive summarizations of distinctive characteristics of Big Data and, by focusing upon its key properties, serve excellently as a basis for a Big Data management discussion. Starting with Volume, Velocity, and Variety, the Big Data property list has been extended to further include Veracity and Value, Volatility and Validity (Khan et al., 2014), and Vulnerability, Variability, and Visualization (Firican, 2017). It is the big volume and high rates at which Big Data is made available, the wide range of available types and formats, trustworthiness of the sources of Big Data, potential inconsistencies in the data, and its lifespan along with security and privacy issues that pose challenges for Big Data management at various levels.

The digital revolution is transforming agriculture, and the advent of new technologies increases the amount of data collected. The term agricultural Big Data refers to the variety and volume of data collected either directly in the field or from other sources. Chi et al. (2016) support the "Vs" approach by defining data in terms of volume, velocity, variety, and veracity:

- Volume: refers to the size of data collected for analysis.
- Velocity: measuring the flow of data and the time frame when it is useful and relevant.
- Variety: reflecting the frequent lack of structure or design to the data.
- Veracity: reflecting the quality, reliability, accuracy, and credibility of the data (Chi et al., 2016).

Although the "Vs" can describe big agricultural data, their analysis does not have to satisfy all dimensions (Rodriguez et al., 2017). Terms of big agricultural data are more about the combination of technology and advanced analytics than just the volume of data that creates a new way of processing information in a more useful and timely manner (Coble et al., 2018).

The following sections present information on capturing agricultural data and tools to perform data management and data analytics, including machine learning techniques. However, since the data revolution hasn't reached every agricultural sector yet and Big Data and AI are not yet specific to orchards and vineyards, the following description is general to all horticultural systems, including orchards and vineyards.

9.2.1 Sensing and Monitoring

The digital revolution transforms agriculture by using modern machinery, computerized tools, and emerging information and communication technologies (ICTs) to improve decision-making and productivity. The evolution and revolution in agricultural Big Data come from the expansion of small agricultural data. Growers can collect data about their operations by spreading several cutting-edge techniques and technologies. Vast amounts of agricultural data and many datasets are collected from GPS and remote sensing to artificial intelligence and machine learning, robotics, and the Internet of Things (IoT). Agricultural data originate from various sources, including:

- Farmers' fields utilize ground sensors, such as weather stations and soil sensors.
- Handheld crop sensors or tractor-mounted sensors.
- Data from aerial sensors, namely, unmanned aerial vehicles, airplanes, and satellites.
- Governmental and third-party organizations gather spatial and temporal historical data or distribute it via online repositories and web services.
- Real-time farm data via online web services and crowdsourcing-based techniques from mobile phones.

Challenges Related to Big Data in Horticulture

The basis for enhanced and effective decision-making is the availability of timely, high-quality data. The demand for large volumes of data and the lack of significance of limited amounts of data create challenges in developing Big Data applications in the agriculture sector, especially in orchards and vineyards. In addition, the sources mentioned above are mostly heterogeneous. The data are represented in different types and formats and differ in volume and velocity and in the way they are updated and governed (Kamilaris et al., 2017).

Most agricultural data sources are fragmented, difficult, and time-consuming to use. At the individual farm level, many digital agriculture applications are not true Big Data applications. Therefore, data errors may be a critical limiting factor in the utility of farm management information systems. Data errors can arise from multiple sources, including low-quality data and errors associated with poor data analytics and processing. This suggests that the full potential of such data and information is not being completely utilized. Integrating a variety of data into a coherent management information system is expected to remedy this situation (Fountas et al., 2015a).

A range of indicators suggests that the availability of farm-level sensors and other precision agriculture technologies, such as mapping and tracking technologies, have already changed the management of many farming systems. Effective collection, storage, sharing, and use of data can support farming decisions toward increased yield and quality of agricultural products and decreased use of inputs, thus increasing profitability and sustainability of farming. However, technical and governance barriers to collecting, storing, and transferring data hinder farmers' transition to digital agriculture. Various management systems, database network structures, and software architectures have already been proposed to improve functionality.

9.2.2 Data Management

Data utilization and decision-making about the application of targeted crop management and harvesting methods are at the core of precision agriculture, which is defined as "a holistic and environmentally friendly farming strategy in which practitioners can vary cultivation and input methods to match varying soil types and cross conditions in a field" (Srinivasan, 2006) to increase "the number of (correct) decisions per unit area of land per unit time with associated net benefits" (McBratney et al., 2005). However, the continuous evolution of digital devices' and infrastructures' capacities to capture and stream data of various formats and types at ever-increasing rates has led to a shift from precision agriculture to smart farming, a novel paradigm of data-driven holistic farm management (Pivoto et al., 2018; Vermesan & Friess, 2016). Smart farming does not rely exclusively on data collected in the field but rather views farm management decisions and operations from a broader perspective of context- and situation-awareness (Wolfert et al., 2017), which can be developed through systematic processes of sourcing, integrating, processing, and analyzing agricultural Big Data.

Nowadays, FMIS has increased in sophistication through the development and integration of new technologies and advances in hardware and software capabilities of mobile phones. Web- and app-based applications enable real-time data recording and automated data transfer (Fountas et al., 2015a; Nikkilä et al., 2010; Peets et al., 2012). Cloud-based FMIS improves operational planning and optimizes the work performed in the fields (Ampatzidis et al., 2016; Kaloxylos et al., 2014). Cloud platforms and cloud computing improve flexibility and accessibility, reduce infrastructure, and streamline processes while offering possibilities for large-scale storing, preprocessing, analysis, and data visualization (Barrett et al., 2014; Nativi et al., 2015). In many cases, computational capacity, both in terms of speed and volume, allows to conduct novel analysis on large volumes of data and use it for actionable decision-making previously not possible (Coble et al., 2018).

Various technologies directly linked to smart farming can be used for data collection and transmission to processing and storage. However, technology requirements for (agricultural) Big Data exploitation and management go far beyond the capacities of a single machine. Therefore, to take full advantage of agricultural Big Data and smart farming necessitates the deployment of systems and services on top of technologies that can handle the complexities of Big Data. One such technology is Apache Hadoop (https://hadoop.apache.org/), a state-of-the-art distributed framework consisting, among others, of three core components, including (i) HDFS (i.e., Hadoop Distributed File System) for handling data storage, (ii) YARN for resource management and optimization, and (iii) MapReduce for workload distribution across multiple nodes of commodity hardware.

Another typical example of cutting-edge Big Data technology is Apache Spark (https://spark.apache. org/), a "fast and general-purpose cluster computing platform" designed mainly for the execution of computations in memory. Apache Spark can also run applications on disk more efficiently than MapReduce and accommodate real-time processing of large sets of streamed data. It can easily be integrated with other tools in the Hadoop ecosystem and thus exploited in various architectures while accessing via custom APIs in widely adopted programming languages, such as Java, Python, Ruby, and SQL.

Other storage solutions for Big Data, tailored to different data structures, are provided by NoSQL databases which have gained momentum against traditional relational database management systems (RDBMSs) in recent years. According to Tiwari (2011), "NoSQL is used today as an umbrella term for all databases and data stores that don't follow the popular and well-established RDBMS principles and often refer to large datasets accessed and manipulated at web-scale" (Tiwari, 2011). There are several different NoSQL data store types, each of which adopts a specific data model (e.g., key-value pairs, column-based, document-based, and graph data models) to best accommodate the particularities of the data structures they have been designed for. Scalability, efficiency, flexibility, high access rates to data, and availability of a range of data models targeting different storage needs are some of the NoSQL data store system advantages over traditional RDBMSs (Nayak et al., 2013).

Another concept that is highly relevant to the need for efficient Big Data storage infrastructures is that of data lakes. Data lakes can be conceptualized as repositories containing large collections of loosely annotated data ingested from various sources (Hai et al., 2016). The key idea behind data lakes is to create collections of various types of data available to be integrated on-demand and utilized to create actionable insights and value. Apart from data extraction and ingestion, it is also necessary to extract metadata from data sources to efficiently support data reasoning, query processing, and data quality management (Hai et al., 2016).

Increased demands for Big Data storage and processing coupled with the high costs for in-premise hosting/maintenance of hardware and difficulties in setting up and configuring Big Data tools have led to a market for cloud-based processing and storage services. Cloud computing platform providers, such as Amazon AWS, Cloudera, and MapR, offer on-demand access to storage and integrated suites of analytics tools under Platform-as-a-Service (PaaS) and/or Infrastructure-as-a-Service (IaaS) schemes, tailored to a range of individual and corporate needs. With access to easily configurable solutions, users can design and execute resource-intensive tasks without worrying about parameterization and workload optimization.

9.2.3 Big Data Analytics

Big Data analytics is the complex process of examining large and diverse amounts of data to uncover information such as hidden patterns, correlations, market trends, and various other insights that can help organizations make informed decisions. Data analysis is categorized into five different stages:

1. **Identification of required data types**: *Find what you want to analyze and determine the questions you want to ask.* Having the solution to a problem in mind, Big Data analytics is a means to an end. Therefore, the solution process needs to commence by identifying what data needs to be collected to gain data-driven insights. The discussion about required data is not confined to formats and types but involves data sources that should be accounted for.
2. **Data acquisition/collection**: *Collect data and determine which is best to use. Having answered the question about the data that should be collected, the following step is to proceed to the actual data collection.* Many issues should be considered as part of this step. For example, data may have to be extracted from multiple databases and stored in a central repository. In this case, setting up ETL (i.e., extract-transform-load) processes is necessary. Other scenarios may involve real-time or near real-time processing. Streaming technologies or systems for temporary data storage are, in such cases, issues to be considered. When it comes to large raw data streams, we may also have to encounter data relevance issues. This means that not all data is important. Thus, filtering out irrelevant data is critical for optimal resource utilization. Yet, filters need to be carefully selected to avoid discarding useful information.
3. **Data preprocessing**: *Identify anomalies and correct duplicates, missing entries, or inconsistent data. Put in place standards to ensure data entry is consistent, but also expect that you will need to do regular maintenance over time.* Data cannot be provided as input to analytics algorithms in its raw form because we need to integrate and aggregate data available in different formats. Apart from that, there may also be errors and inconsistencies. Format conversion and data cleaning are core to this step. Data anonymization is also an issue to consider when the data includes sensitive personal details.

4. **Analyze**: *Several data analysis methods can be considered depending on the problem.* In this context, a discussion of different kinds of Big Data analytics is applicable. An outline of the different types of data analytics is provided below:
   - Descriptive analytics focus on answering questions about who, where, what, when, and how many.
   - Diagnostic analytics is concerned with responding to queries about why something happened.
   - Predictive analytics investigates and identifies trends in relationships between variables, determines the degree of relationships' correlation, and hypothesizes causality.
   - Prescriptive analytics focuses on investigating future scenarios and attempts to give answers to what-if questions and subsequently propose courses of relevant actions. Machine learning models based on Big Data play a significant role in this endeavor as they allow the prediction of outcomes considering a range of variables.
5. **Interpretation of data analysis results**: Once you have the data and understand it, what can you do with it? The final step is about making decisions and taking action regarding problem-solving. To successively do so, developing an understanding of analysis outcomes is necessary. Results' reports and visualizations have the potential to facilitate data-driven insights and, thus, inform problem-solving actions.

The scientific discourse on Big Data goes hand in hand with the extraction of value. As Gandomi and Haider (2015) characteristically point out, "the potential value of Big Data is only unlocked when leveraged to drive decision making." Yet, to "enable evidence-based decision making, there is a need for efficient processes to turn high volumes of fast-moving and diverse data into meaningful insights" (Gandomi & Haider, 2015). This is the exact point at which Big Data analytics comes into play. Exactly like in the case of Big Data, there are several definitions of Big Data analytics found in the literature. A brief review of this reveals that the term focuses on applying fit-for-purpose analysis methods and tools tailored to the particular characteristics and properties of Big Data. Starting from the need to solve a problem, the intention is to acquire actionable insights and knowledge to support decision-making and arrive at a problem solution. However, the extraction of knowledge from Big Data is not a one-step process. It involves multiple interconnected steps needed to be executed, most of the time, in an iterative fashion until outcomes are reached. This chain of Big Data analysis-related tasks is illustrated in a straightforward manner in a definition, according to which (Big) data analytics is "the process of extracting, transforming, loading, modeling, and drawing conclusions from data for decision-making."

It is important to investigate how existing Big Data analytics methods fit with agricultural Big Data and the knowledge needs they are collected for. According to Coble et al. (2018), machine learning, artificial neural networks (ANNs), decision trees, and clustering are some methods and tools that can be exploited for agricultural Big Data analysis purposes. For example, by utilizing available weather data, machine learning can be exploited for building weather forecasting models aiming to support decision-making by farmers. Other machine learning applications are linked to crop disease protection and crop yield prediction and selection. Clustering methods (e.g., K-nearest neighbors), decision trees, and ANN models can also facilitate crop yield prediction and selection. Irrigation-related models (built upon rainfall and water level predictions) and price prediction models (based on crop production outputs, input cost changes, market demand and supply, market price trends, wages, and costs of cultivation, transportation, and marketing) can also be built with the help of ANNs. Kamilaris et al. (2017) contribute to the discussion on the potential use of Big Data analytics in agriculture by linking specific sectors to agricultural Big Data sources and Big Data analytics (Kamilaris et al., 2017). Machine learning methods and tools, such as clustering, decision trees, support vector machines, logistic regression, and artificial neural networks, are prominent with applications in weather and climate change, land use, weed control, animal research, crops and soils, and food security and availability. Analytics tailored to geospatial data is core to the sectors of remote sensing, food security and availability, and weather and climate change. In addition to the above, interesting use cases for advanced image recognition and processing concerning weed control, remote sensing, and land use-related applications can be found.

9.2.4 Machine Learning

Machine learning (ML) is a branch of computer science, an application of artificial intelligence, which gives computers the ability to learn without being explicitly programmed. It can be used to construct various mathematical algorithms to exploit the potential value of Big Data, which makes learning possible.

Machine learning is comprised of a two-step process. The first process involves the machine "learning" the input data, and in the second process, the machine translates and analyzes both the input and output data. This leads to the creation of machine algorithms that then construct a system model to predict future values.

9.2.4.1 Types of Machine Learning Algorithms

There are three types of machine learning algorithms:

1. **Supervised learning (SL)**: When input and output variables are provided, learning becomes supervised. In this type of ML, the algorithm uses various training examples, and the machine analyzes the inputs and corresponding outputs. More widely used SL algorithms include artificial neural networks, decision trees, K-means clustering, support vector machines, and Bayesian networks. SL is further divided into two subparts, regression and classification, as explained below.

Regression: The output data can be continuous (i.e., in the range of 0–5000) or percentage-wise. Let's take the example of predicting downy mildew disease in vineyards and approaching this as a simple regression problem. Based on the agronomic knowledge, humidity is a parameter that escalates the downy mildew presence and expansion. Thus, using regression analysis, we can correlate the severity of disease presence to the air humidity measurements. Data from previous years will provide humidity measurements (x) and disease presence (y). So, a function $y = f(x)$ will be established considering a specific regression order that shows how accurately we fit the regression to our reference data x, y. Based on the relevance of the new input humidity measurements (xi) and the regression order, we can predict the severity of the disease (yi).

Classification: The output data is in discrete form, i.e., 0, 1, 2, but it should not be a fraction. Using the example of apple scab disease, we assign images of healthy leaves to class 0 and images of infested leaves to class 1, when using cameras to detect the problematic areas (Fig. 9.2). The classifier in this example is the k-nearest neighbor (k-NN). Each image is accompanied by a set of features, in most cases (i) color features, (ii) shape features, and (iii) texture features. Considering that apple scab appears as visible color anomalies on leaves, we expect major differences in color features during the classification process.

Consequently, in the training phase, we defined a set of features associated with healthy apple leaves (class 0) and apple scab leaves (class 1). So, in every new apple image of an unknown class, the features are calculated, and this observation will be placed on the feature map. We consider a 2D feature plane with a y-axis for color features and an x-axis for shape features. Depending on the k-nearest features ($k = 1$ in the example), the new observation is assigned either in class 0 or 1, **based on its proximity to the already known classes ($d_{\min}$)**.

2. **Unsupervised learning (UL)**: Here, we provide data whose input is known but whose output is unknown. Techniques such as clustering, which groups data into

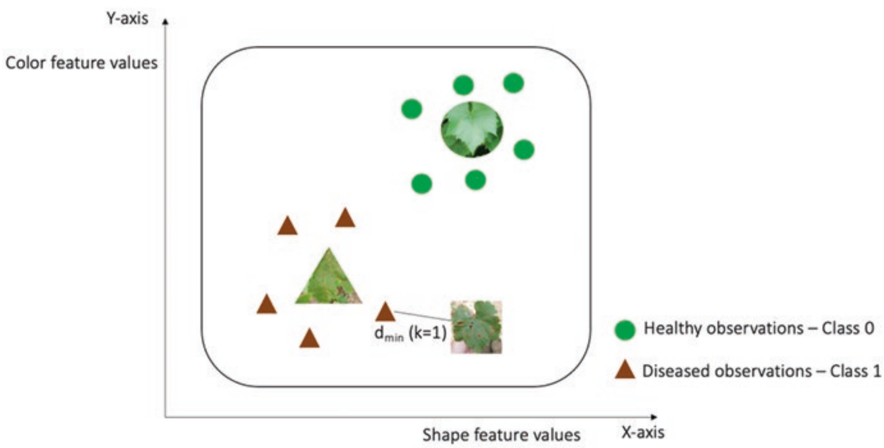

Fig. 9.2 k-nearest neighbor classification example

separate classes, are popular in this analysis. More widely used UL algorithms are self-organizing map (SOM), partial-based, hierarchical, K-means, COBWEB, and density-based spatial clustering. Applications using UL detect anomalies that do not fit any group or segmented datasets by some shared attributes. For example, DBSCAN is a clustering method that employs density and topology information to segment vegetation pixels from bare soil pixels in many agriculture vision applications.

3. **Reinforcement learning (RL)**: This is a special type of machine learning that focuses on learning through penalties and rewards. It is mostly implemented in video games and robotics. The learning process for RL is based on the principle of feedback. The idea is that every action impacts the system, which is then reported back to the algorithm, modifying its behavior. Exposing the fundamental concept of this method used in orchard and vineyard farming, many agriculture robots learn from mistakes such as colliding with obstacles or failing to pick fruit through penalty scores. At the same time, they figure out the shortest path to bypass obstacles or grab a fruit with the minimum number of motions through rewarding optimum practices.

All the methods mentioned above constitute different approaches to increasing the intelligence of a computing system. Another term often used in the artificial intelligence world is deep learning (DL). DL is a subset of machine learning and refers to the computer software technique that mimics the network of neurons in a brain. Deep learning co-exists with the learning methods listed above but offers great advantages in feature extraction and prediction accuracy.

9.2.4.2 Application Domains

ML provides a powerful and flexible framework for data-driven decision-making and the incorporation of expert knowledge into the system. These are some of the key characteristics of the ML techniques that make them widely used in many domains and highly applicable to precision agriculture (Chlingaryan et al., 2018).

Covering a large portion of ML applications in agriculture, a recent study indicated (i) crop management, including applications for yield prediction, disease and weed detection, crop quality, and species recognition; (ii) water management; and (iii) soil management as the most important categories in the farm management cycle (Liakos et al., 2018). The following section will showcase ML applications covering the categories that play a crucial role in the orchard and vineyard production cycle.

For yield prediction purposes, a study on coffee trees employed 42 color features in digital images and supervised learning methods to count the fruits on the branches and provide information on the maturity stage and weight in each measurement (Ramos et al., 2017). Another approach focusing on yield prediction in apples with unsupervised learning offered promising results by considering the driving factors affecting yields, such as soil texture (clay and sand content), soil electrical conductivity (EC), and potassium (K), phosphorus (P), organic matter (OM), calcium (Ca), and zinc (Zn) content (Papageorgiou et al., 2013). In grapevines, a 3D imaging technique combined with ML managed to estimate the yield accurately before ripening with 98% accuracy and 96% during ripening (Dey et al., 2012).

As far as disease detection is concerned, ML has found fertile ground in many applications related to detecting diseased leaves and fruits accurately. Color cameras provide useful color, shape, and textural information that allow the ML classifiers to decide if the content of an image belongs to the healthy or diseased class. But what happens when the visible spectrum cannot reveal evidence of disease? Multispectral, hyperspectral, and thermal cameras provide more sophisticated information on the crop reflectance, allowing the effective detection of diseases even at the presymptomatic stage when disease stress is not visible to the naked eye. Such research concepts are tested in diseased crops, including citrus (Sankaran & Ehsani, 2013), banana, lemon, and mango (Arivazhagan et al., 2013), and downy mildew and black rot diseases in grapevines (Waghmare et al., 2016). However, the unstructured field environment challenges the field deployment of such computer vision techniques. Fruit occlusion and poor lighting conditions are the major problems that vision-based systems are suffering.

Crop quality is another application domain of ML that facilitates the accurate crop status assessment. For example, unsupervised learning techniques utilized soil data (e.g., electric conductivity) and NDVI measurements to estimate grape quality and effectively delineate into separate farm management zones (Tagarakis et al., 2013). In pear orchards, hyperspectral imaging and supervised learning techniques were used to discriminate deciduous-calyx pears (high quality) from persistent-calyx pears (low quality) (Hu et al., 2017).

Regarding water management in orchards and vineyards, several studies have been conducted to estimate daily, weekly, and monthly evapotranspiration. This is a complex process that requires sufficient water resource management and the effective design of irrigation systems. ML techniques are ideal tools for understanding patterns and sequences of meteorological data; thus, two studies used temperature records from 1961 to 2014 (Feng et al., 2017) and 1951 to 2010 (Mehdizadeh et al., 2017) to estimate evapotranspiration. Finally daily dew point temperature is an important element for identifying expected weather phenomena, so a relevant study employed ML techniques to estimate daily dew temperature, having two local weather stations as a source of input data (Mohammadi et al., 2015).

Finally, soil properties such as soil drying, condition, temperature, and moisture content are pivotal elements of the production cycle, while the mechanisms and processes are difficult to be determined. ML has proven to be a promising tool in identifying the soil status since soil measurements are generally time-consuming and expensive for mapping the soil properties in large-scale vineyards and orchards. One notable study managed to estimate the daily soil temperature at six different soil depths of 5, 10, 20, 30, 50, and 100 cm (Nahvi et al., 2016), while another research used ML techniques to predict soil moisture only from the force data derived from tillage machines and the working speed (Johann et al., 2016).

9.3 Decision-Making and Intervention

In data-driven agriculture, high-quality data is the most valuable currency in the sector. Producers need an enormous amount of information to enable efficient planning and decision-making throughout the entire growing season. Nutrient deficiencies, water stress, and disease occurrence can be effectively managed during the growing season (Usha & Singh, 2013). These problems can be solved with constant data sources that provide valuable information on crop health and stress, nutrient requirements, and infestation threat levels. However, the challenging aspect of the agricultural sector is that data loses value the later it becomes available. Decisions such as disease control or inputs application require utmost accuracy in their timing, with a miss of a few days resulting in major losses in the final yield. Therefore, agricultural decision-makers at all levels need an increasing amount of information to better understand the possible outcomes of their decisions and to assist them in developing plans and policies that meet their goals.

Many decision support systems (DSS) have been developed, and farmers have shown great interest in limiting uncertainty in decision-making (Stone & Hochman, 2004). However, DSS-related "problem of implementation" remains in many cases because of the "lack of sustained use in a way that influences practice" (McCown, 2012). Factors that may influence the implementation of a DSS in agriculture include profitability, user-friendly design, the time requirement for DSS usage, credibility, adaptation of the DSS to the farm situation, information update, and level of knowledge of the user (Kerr, 2004).

Even though most of the technical problems related to DSS (farmer's access and connectivity issues) have been solved during the past few years (Rossi et al., 2014), the following restrictions remain and could be the next challenge for the future developers of agricultural DSS: (a) they often fail to see crop production holistically, and most DSS is problem-specific; (b) they have poor quality because of insufficient validation; (c) they could be more user-friendly; (d) they are time-consuming, because of delays in data processing or complex input requirements; (e) information is sometimes delivered to users asynchronously related to decision-making timing and the need for action; (f) there is a need for constant maintenance and updates; (g) they have low capacity of modification and customization; and (h) they often describe a result as the optimal solution which is discouraging to the farmer who usually wants to take part in the decision-making process.

9.3.1 Agricultural Decision Support Systems (DSS)

Agri-information systems can be defined as a system for collecting, processing, storing, and disseminating data in the form needed to carry out a farm's operations and functions or providing farmers with valuable information to support decision-making and farm management. Agricultural decision support systems (DSS) are computing systems that help decision-makers leverage field data and agronomical models to solve problems and develop carefully planned strategies to meet their production targets. Sophisticated DSS aims to improve the performance of agricultural production units by analyzing enormous volumes of information and translating it into complex decisions that often cannot be made by human means.

Spatial DSS (SDSS) are computer-based systems designed to solve complex problems related to multiple parameters that demonstrate spatial variability. Typically, an SDSS consists of a geo-informatic system (GIS) and a DSS. Geospatial cyber-infrastructure (GCI) is the most current version of a DSS, using data resources, network protocols, computing platforms, and computational services. They support functionalities such as data acquisition, storage, management, and integration of both static (e.g., pedology, geology) and dynamic data (e.g., daily climate), data visualization, and on-the-fly computer applications (such as those enabling simulation modeling for the determination of water stress), all potentially accessible via the web (Terribile et al., 2017).

In general terms, most DSS used in agriculture have similar basic architecture:

- Collection, organization, and integration of several types of information required for producing a crop or describing complex multifactorial processes in agricultural units. Data is entered either from the farmer, via the web, which provides site-specific information, for each field decision unit, or obtained automatically (often in real time) by sensors positioned on the farm. In general, these data may include cropping and plant parameters (dimensions, growth stage, reflection of light in certain frequencies), field data (altitude, sun exposure), soil data (dynamics, temperature, water, nitrogen, salinity, carbon balance), climate data (temperature, humidity, rainfall, direction and strength of wind), and farm management practices (irrigation, fertilization, pest control).
- All this information is then analyzed and processed, usually by a server, as part of a web infrastructure in most cases that provides output to the farmer to support his field management. The processing and interpretation of the data are facilitated through crop models, classified as either empirical/statistical or dynamic. Empirical models usually exploit the statistical relationship between all parameters mentioned above; they are computationally demanding (e.g., regressions) and are widely accepted (Terribile et al., 2017). However, they have various weak points, such as the high level of calibration required (when applied to a new environment). Most importantly, they do not address the nonlinear relationships between plant and environmental factors. On the other hand, dynamic models attempt to solve the nonlinear relationships and allow for greater generalization of crop growth processes and, consequently, a better adaptation to new environments and an overall much better performance. Generally, dynamic models simulate plant growth development daily and consider site features at specific locations (Terribile et al., 2017).
- After processing and interpretation, depending on the type of the DSS, it may recommend the most appropriate action or action choices. Depending on the type and specificity of the DSS, these suggestions could concern (a) planting dates based on soil and weather conditions; (b) harvest dates based on maturity, along with soil and weather conditions; (c) daily irrigation based on daily values or soil

water depletion; (d) fertilizer additions, based on read-in values or automatic conditions; (e) application of residues and other organic materials (plant, animal); (f) prevention steps if disease risk is detected; and (g) both daily operational and long-range farm-related strategic decisions.

9.3.2 Types of Agricultural DSS

9.3.2.1 Irrigation DSS

Regulated deficit irrigation (RDI) is a strategy in which water is saved by reducing or completely restricting irrigation at certain crop growth stages to control the growth of shoots. This technique has been widely used for many decades to increase the quality of fruit yields; however, its application in drought-sensitive orchards carries the risk of imposing too much water stress. For this reason, DSS is often used when such practices are adopted to ensure that no critical mistakes occur when accuracy matters the most. Marsal and Stöckle (2012) carried out an experimental pilot to test the efficiency of CropSyst in a pear orchard where an RDI program was applied. The model performed exceptionally well, especially for the period after applying deficit irrigation (Marsal & Stöckle, 2012). In 2012, Peets et al. described the development and validation process of a GIS-based SDSS for precision irrigation management of tree crops. Their system combined crop growth data generated by various field sensors under environmental conditions and irrigation regimes in orchards with abiotic soil, elevation, and climatic data to construct a site-specific orchard irrigation DSS.

9.3.2.2 Fertilization DSS

Excessive use of fertilizers has both environmental and economic impacts. The farmer spends money without improving his yield, and increased concentrations of nutrients in the soil often cause phytotoxicity, which leads to yield decrease and quality degradation. On the other end, the under-application of fertilizers does not allow the crops to reach their maximum productivity since available nutrients are not sufficient for their needs. Both cases result in low nitrogen use efficiency.

Fertilization DSS is based on agricultural models after vigorous tests on a large number of fertilization experiments for each crop type. Therefore, the ability to estimate the optimal application rates and dosages for each fertilizer application is essential for efficient farm management (Papadopoulos et al., 2011). Figure 9.3 shows a commercial application of a crop management platform and a decision support system with the proposed variable rate fertilization that can be visualized.

Fig. 9.3 A pH soil map of a vineyard (top image) and a "Precision Farming Project" suggesting variable rate fertilization of the field (bottom image), as suggested by ABACO's SITI4farmer DSS

9.3.2.3 Pest Management DSS

The pest control methods and timing require deep knowledge of pests and the mechanisms that affect their spreading, setting pest DSS as an essential part of pest management programs. Advanced integrated pest management (IPM) programs require complex tactical decisions for planning and execution. Agrochemicals are often applied when there is no actual infestation and when the farmer decides when to spray. Therefore, knowledge derived from field data is needed to enable accurate decisions on pest management.

9.3.3 Examples of DSS in Agriculture

Many new technologies have been developed for or adapted to agricultural use in the last 30 years. The most recent information systems that support agriculture decisions allow the segregation of minor differences, both objective and statistically significant. Existing tools are even now designed to better manage crop adaptation between different parcels, focusing on the variability within the parcel. Many of these processing systems have been initialized in the framework of research projects, but they are often transformed into commercial services offered to single farms.

DSSAT (Decision Support System for Agrotechnology Transfer) is a software application program for simulating crop models which incorporates models for 42 different crops, in constant development, since its beginning as a research program. It has a modular structure with multiple components, including soil, crop, water, weather, soil-plant-atmosphere competition, management, pest control module, etc.

Many DSS have been developed especially for vineyard management, research, and commercial purposes. Vite.net is a research project in Italy developed for the sustainable management of vineyards and is intended for the vineyard manager (Rossi et al., 2014). The DSS consists of two main parts: (i) an integrated system for real-time monitoring of vineyard components (air, soil, plants, pests, and diseases) and (ii) a web-based tool that analyzes these data by using advanced modeling techniques and then provides up-to-date information for managing the vineyard in the form of alerts and decision supports. GeoVit (Terribile et al., 2017), developed as a GCI, may provide an important web-based operational tool for high-quality viticulture as it better connects the farm and landscape levels. It supports the acquisition, management, and processing of static and dynamic data, data visualization, and computer applications to perform simulation modeling, all potentially accessible via the web. The NAV (Network Avanzato per il Vigneto – Advanced Vineyard Network) system is a wireless sensor network (WSN) designed and developed for remote real-time monitoring and collecting micro-meteorological parameters in a vineyard. VineSens is a hardware and software platform for supporting pest management decision-making. Using a WSN and epidemiological models can predict and prevent diseases, most usually faced by vine growers, such as downy mildew. In commercial services, several companies offer solutions for monitoring and managing vineyards, combining hardware and software with most of them provided and supported through web-based platforms, such as VintiOS, a precision viticulture software, supporting vine growers and oenologists on the grapevine production and quality.

9.4 Discussion and Conclusions

This chapter presented an overview of farm management information system (FMIS) principles that integrate sensing, data management and analysis, and decision-making to automate the operation and management of modern orchards and vineyards. It investigated how existing emerging technologies, such as Big Data analytics methods and machine learning, fit with agricultural Big Data for tree fruit orchards and vineyards and the knowledge needs for which they are collected.

Farmers need an effective way to manage large volumes of information and technological tools to assist them in making year-round optimal and sustainable decisions. The integration of a variety of data into a coherent management information system is the solution. Farm management information systems support the collection, processing, and storage of data in a form that enables accurate scheduling and execution of farming operations or provides farmers with valuable information to support decision-making. The availability of farm-level sensors and other precision agriculture technologies has changed the management of many farming systems. Nowadays, FMIS has increased in sophistication through the development and integration of new technologies and advances in hardware and software capabilities of mobile phones. Web- and app-based applications enable real-time data recording and automated data transfer. Several technologies directly linked to smart farming can also be used for data transmission, processing, and storage.

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Chapter 10
Economic and Societal Aspects

Zachariah Rutledge and J. Edward Taylor

Abstract This chapter discusses economic and societal aspects of automation in tree fruit orchards and vineyards. We start by explaining economists' views on the drivers of technology development and move to a discussion about the social welfare implications of automation under scenarios of farm labor abundance and scarcity. We also discuss the relationship between economic development and the societal transition out of farm work, how farm labor scarcity influences farming decisions, and how economists model the decision to adopt labor-saving technologies. We conclude with some thoughts about the possibility of a future with advanced robotic harvesting systems operated by highly skilled personnel.

10.1 Introduction

In 1984, a group of small farmers and community activists, together with 19 farm workers, sued the University of California (UC) for developing a new harvesting technology that revolutionized the production of processing tomatoes. The plaintiffs argued that the University's agricultural research program "displaces farm workers, eliminates small farmers, hurts consumers, impairs the quality of rural life, and

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impedes collective bargaining."[1] The case eventually settled, but it cost the University of California dearly and put a damper on labor-saving agricultural research and development for more than two decades. The US Secretary of Agriculture Robert Bergland famously stated: "I will not put federal money into any project that reduces the need for farm labor" (Sarig et al., 2000).

The UC tomato harvester case was the product of an era in which farm labor was abundant and wages for farm workers were stagnant or decreasing. Today, US farmers face a different world in which the number of people willing to work in orchards and fields is diminishing and real farm wages are on the rise. Nevertheless, the case highlighted the potentially far-reaching social implications of labor-saving technological change, and it left behind a legacy of suspicion that mechanization might be antithetical to the welfare of workers, consumers, and the communities in which they live.

This chapter explores economic and social aspects of advanced automation in tree fruit orchards and vineyards. It begins by explaining economists' views on the social welfare effects of automation under different labor market scenarios, in particular, when agricultural workers are abundant and when they are scarce. Next, it traces the evolution of a farm labor market going through the transition from labor abundance to labor scarcity by examining the case of California and sharing new research findings on how farmers are adapting to a diminishing farm labor supply. When agricultural labor is abundant, automation may be detrimental to agricultural workers and small farmers who cannot afford to invest in new technologies, even if the total benefits to society are positive. On the other hand, in the current era of labor scarcity, labor-saving automation is more likely to create benefits for workers and consumers as well as for agricultural producers and society as a whole. We conclude by imagining a future with robots in the fields and what this is likely to portend for workers, consumers, and rural communities.

10.2 Economic Views on Automation and Social Welfare

Broadly speaking, the widely held view among economists is that producers adopt new technologies when the expected cost savings from doing so exceed the investment cost. Adoption is only one part of technology change, however, because new technologies need to be developed before adoption can take place.

There is some disagreement about the determinants of technology development. The induced innovation hypothesis posits that changes in relative factor (input) prices determine technology development. This hypothesis was first advanced by economist John Hicks in his classic work *The Theory of Wages* (1932). Hicks wrote:

[1] See California Agrarian Action Project, Inc. v. Regents of the University of California (1989).

> A change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind—directed to economizing the use of a factor which has become relatively expensive.

For example, in a labor-abundant environment, wages are low relative to capital and land rents, so there is little incentive for public and private entities to invest their resources in developing labor-saving technologies. In a labor-scarce environment, rising wages relative to rents create incentives to develop labor-saving technologies as well as for farmers to adopt those technologies once they are "on the shelf."

Advocates of induced innovation point to the so-called "Green Revolution" high-yielding grain varieties that gained wide acceptance in Japan, where land was relatively scarce. Growth in agricultural output in continental Europe, which increased at twice the rate of the USA, was also driven by rising grain yields (Binswanger, 1986). Early improvements in wheat and rice varieties were developed by the International Maize and Wheat Improvement Center (CIMMYT) in Mexico and the International Rice Research Institute (IRRI) in the Philippines, which eventually led to the inception of the Consultative Group on International Agricultural Research (CGIAR) (Pingali, 2012). Rising world food demand, fed by population and income growth, induced institutions like the CGIAR and the Rockefeller Foundation to invest in R&D to increase yields per acre of land. In contrast, mechanical innovations were central to the history of grain production in the USA, where land was relatively abundant and the cost of capital was low.

An opposing view is that research and development is largely an exogenous, self-perpetuating process, as new breakthroughs lead to others that, in turn, lower the costs of developing new technologies over time. UC researchers developed the tomato harvester in an environment of labor abundance and low agricultural wages, exploiting new developments in mechanical and agronomic engineering. It is difficult to argue that relative prices of labor and capital led to Jobs' and Wozniak's invention of the personal computer or the iPhone, which would not have been possible without prior advances in transistor and wireless technology. Once they became available, though, adoption was explosive.

Some economists have attempted to test whether relative factor prices explain the development of new technologies, consistent with induced innovation, with mixed results. Figure 10.1 depicts the factor prices for labor and capital inputs (real wages and interest rates), revealing a pattern (i.e., a rising wage to interest rate ratio) that is consistent with the induced innovation of labor-saving technologies. Examples of studies that find support of the induced innovation hypothesis include Thirtle et al. (1995) in South Africa, Bidabadi and Hashemitabar (2009) in Iran, and Hyami and Ruttan (1971) in the USA. However, examining data at a more granular geographical level in the USA, Olmstead and Rhode (1993) only found evidence of induced innovation in certain regions of the USA but not in others. This led them to argue that the induced innovation hypothesis was insufficient to fully explain the development of American agriculture and that other factors must have also played a role. Others argue fervently that technological determinism is the main driver of R&D and that it is becoming more important over time (e.g., Arrow, 1962; Levin, 1988).

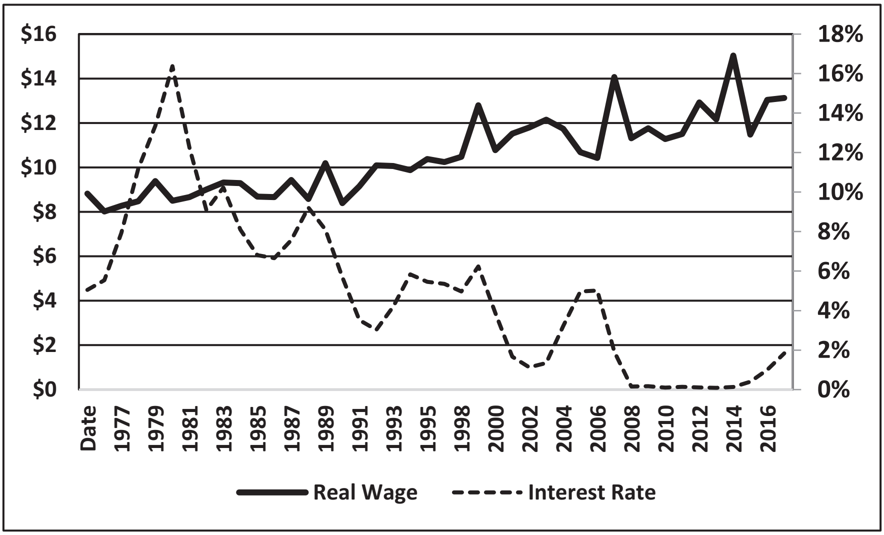


Fig. 10.1 Real US farm worker wages vs. federal fund interest rate (1976–2017)
Note: Wage data were obtained from the Current Population Survey (https://ipums.org/). Interest rate data were obtained from the St. Louis Federal Reserve Economic Research Database (https://fred.stlouisfed.org/)

It is likely – to the point of being almost tautological – that a mixture of these two theories is needed to explain the development and adoption of advanced automation in tree fruit orchards and vineyards. Creating labor-saving solutions for delicate, difficult-to-pick fruits is complex and would not be possible without recent advancements in mechanical engineering, machine learning, artificial intelligence, wireless technology, agronomics, and other fields. Additionally, farmers will not adopt new labor-saving technologies unless it is economically feasible and optimal to do so. The economic cost-benefit analysis for adopting new labor-saving technologies obviously depends upon factor prices, including wages. Even if a robot can pick a fresh peach crop as well as a human farm worker, farmers will be unlikely to purchase the robot unless wages are high (and expected to keep on rising) and capital costs (i.e., interest rates on loans to invest in robots) are low.

Asking whether induced innovation or technological determinism drives the creation and adoption of new technologies might seem like an academic exercise, but the answer has potentially far-reaching social ramifications. For example, consider the UC tomato harvester, which was launched into an environment of abundant farm labor and low farm wages. Even though the end of the US-Mexico Bracero program (1942–1964) created some expectations of labor shortages, for the most part, they did not materialize (Martin, 2006a). It would seem that an induced innovation model is ill-suited to explain why the UC tomato harvester appeared when it did. It is difficult to argue that rising relative wages led UC researchers to develop the tomato harvester, as induced innovation theory would posit.

Nevertheless, a stunning drop in labor requirements to harvest processing tomatoes resulted in the almost complete adoption of the tomato harvester in a very short period of time: within 5 years, nearly 100 percent of processing tomato farmers had adopted (Taylor & Charlton, 2019). Despite the high cost of adopting the new technology, the dramatic decrease in labor costs made the tomato harvester a feasible investment for farmers who could afford it. There is no question that the technology displaced large numbers of field workers in this low-wage, labor-abundant environment. The displacement of workers caused a backlash against the UC tomato harvester, which was led by farm worker advocates and small farmers who could not afford to invest in the new technology. There is mixed evidence about whether the adoption of agricultural technologies generates harmful impacts for agricultural workers in developing countries, where a large proportion of the workforce is still engaged in agricultural work. The impacts differ by region and depend on factors such as land availability for farmland expansion and how well markets are integrated. For example, in Bangladesh, mechanization has been linked to higher wages in both the short and long run and does not appear to reduce employment (Hassan & Kornher, 2019). This has been attributed to scale effects, which have led to an increase in the demand for labor. However, in other regions, such as in Ethiopia, Senegal, and Kenya, the adoption of tractor-powered machines has been shown to displace labor (Kirui, 2019).

Technological determinism can result in the development and introduction of labor-saving automation in a labor-abundant environment. Induced innovation, on the other hand, posits that new labor-saving technologies will not be developed unless labor becomes scarce (and expensive) relative to the cost of other factors. It would seem, then, that social disruptions from new technologies are less likely in a world where induced innovation guides technology change compared to the situation where "innovation accidents" lead to the sudden and unexpected appearance of automation, like tomato harvesters and peach-picking robots.

10.3 California Agriculture: From Worker Abundance to Labor Scarcity

Concerned about farm labor shortages during World War II, President Roosevelt signed an executive order that launched the Bracero program, authorizing Mexican laborers (Braceros) to enter the USA to perform contract work on farms (Bracero History Archive, 2019). Over the 22-year duration of the program, roughly 1.5 million Braceros came to work on US farms, many of them returning year after year from poor villages in rural Mexico under different contracts (Martin, 2006b). In addition to this large influx of Braceros, over five million unauthorized Mexicans were apprehended over the same period, suggesting that a significant number of unauthorized workers had also entered the farm labor force (Martin, 2001). This massive inflow of immigrants depressed the wages of native-born workers, which helped opponents of the Bracero program (including President Kennedy) successfully argue for its termination. After the Bracero program was ended by Congress in 1964, Mexicans continued to make the trek north into the USA. The relatively high wages in the USA, coupled with lax immigration enforcement across the southern border and laws that allowed US employers to hire unauthorized workers, enabled undocumented Mexicans to flood the US farm labor market, which led to decades of reliance upon low-wage Mexican workers for tree fruit production and vineyard work.

Attempting to end the massive inflow of undocumented immigrants from Mexico, the US government passed the Immigration Reform and Control Act (IRCA) in 1986, which legalized 1.3 million unauthorized farm workers, established the current H-2A agricultural guestworker visa program, and imposed legal punishments (e.g., fines and jail time) for farmers who knowingly hire undocumented workers. The H-2A visa program allows US farm employers to employ temporary foreign workers when a sufficient number of domestic workers are unavailable. Although its use has increased substantially over the past 10 years, historically it had not been widely used due to the higher cost of employing workers through the program, as well as the complicated nature of the approval process. Nevertheless, the passage of IRCA caused farmers and policymakers to become concerned about the potential for farm labor shortages, prompting the emergence of a body of academic literature. However, farm labor shortages did not materialize after the passage of IRCA, and researchers found that it may have even led to a temporary boost in the farm labor supply, resulting from family reunification policies that granted visas to the family members of unauthorized farm workers who had been recently legalized (Boucher et al., 2007). Despite these previous "false alarms," recent research reveals that the era of farm labor abundance *is* coming to an end.

For at least 10 years, media outlets have provided anecdotal evidence of farm labor shortages in California (and throughout the USA), with some farmers claiming lost income due to an inability to find enough workers during harvest time (e.g., Plummer, 2013; Glaister, 2006; Good, 2017; della Cava & Lopez, 2019; Oatman, 2018). Subsequently, a new body of research has taken root exploring whether the anecdotal evidence can be corroborated with data or if these reports are being blown out of proportion by politically motivated actors. Skeptics argue that farm labor shortages wouldn't occur if farmers simply raised wages. However, some economists argue that local farm labor shortages may occur even when wages rise because agricultural labor markets are local, farm labor is not always mobile, and factors such as weather can affect the timing of regional labor demand shocks when a sufficient number of properly skilled workers are simply not available in the local labor market (Fisher & Knutson, 2012).

In a recent issue of the *American Journal of Agricultural Economics*, Richards (2018) used structural and econometric modeling to study whether there is evidence of farm labor shortages among different classes of farm employees in California, the state with the highest demand for agricultural labor. He found evidence consistent with persistent shortages among harvest workers in recent decades. Hertz and Zahniser (2012) provide evidence of labor shortages by identifying US counties that have experienced extraordinary growth in farm worker earnings yet have had lower employment levels, consistent with a declining farm labor supply. Others have found that the farm workforce is aging and is not being replenished by young immigrant workers (Martin, 2019), immigrant farm workers are settling down in the USA and are less likely to travel to work on farms (Fan et al., 2015; Reyes, 2004), and as the Mexican economy continues to expand, workers are being drawn out of the farm labor pool into other sectors of the economy (Taylor et al., 2012; Charlton & Taylor, 2016; Rutledge & Taylor, 2019b). Moreover, Richards and Patterson (1998) provide an economic rationale that explains why workers leave the agricultural sector and do not return to the sector. Their analysis suggests that farm workers who gain employment in other sectors of the economy must make irreversible investments in human capital or location; thus, compensation in the agricultural sector must rise to a level that offsets those investment costs or workers are unlikely to return.

Immigration policies are also playing a role. Increased security at the southern border has led to higher "coyote" (smuggler) fees, which can cost thousands of dollars and has reduced the number of Mexicans who can afford to cross the border (Orrenius, 2004; Dickerson & Medina, 2017). And those who pay the increased fees often have to take out loans from family members in the USA and end up seeking work in higher-paying non-farm occupations (such as construction) to pay them off. In some parts of the USA, local immigration enforcement policies have driven farm workers out of the local labor market suggesting that, in general, the threat of deportation may also lead to a smaller farm labor supply (Ifft & Jodlowski, 2016; Kostandini et al., 2013). And opposition to immigration by US government officials has been felt by farmers who claim that it has impacted the number of workers who are available (Frank, 2017). These factors have induced farmers to raise wages, reducing the already tight profit margins that they operate on (Rutledge & Taylor, 2019a; Charlton et al., 2019a, b; Hertz & Zahniser, 2012). Even if farmers gave up all of the surplus (profit) they generate through employing farm workers, recent research has found that they would still not be able to raise wages high enough to put an end to the shortages because the increase in wages that would be necessary to attract enough workers exceeds the profits that farmers have to spare (Richards, 2018). In addition, global and national market pressures make it difficult for local farmers to pass increased labor costs onto the wholesalers and retailers who purchase their fruits because commodity prices are not determined locally and farmers generally do not dictate the price they receive for their crops.

Other frictions in the farm labor market arise from the fact that domestic workers are unwilling to perform farm work because of the non-pecuniary costs (Taylor et al., 2012). To highlight this fact, during the recent recession when unemployment rates were close to 10%, the United Farm Workers of America (a farm labor union based in California) launched the "Take Our Jobs" campaign, which offered farm employment to any American who wanted a job. However, even though unemployment rates were the highest they had been in decades, only a few dozen Americans took them up on their offer after realizing that the work entailed "back-breaking jobs in triple-digit temperatures that pay minimum wage, usually without benefits" (quoted from Smith, 2010). This means that the existing pool of workers who are willing to perform farm work is comprised of poor (mainly undocumented) Mexican immigrants who do not have better employment opportunities, of which there is a limited (and decreasing) supply.

The fact that few US-born workers are willing to do farm work underscores this country's relatively advanced position in the economic development process. In fact, the transition out of farm work is common among most countries that have gone through the development process. The response to labor shortages tends to involve importing farm labor from poorer nations.

Figure 10.2a shows a scatterplot of the proportion of each country's labor force in agriculture against the per capita gross domestic product (a commonly used measure of economic development). The beginning of each arrow marks the position that each country was at in 1991, while the arrowheads show the position of each country in 2017. Nearly all of the arrows point to the southeast, indicating that as countries develop and become richer, their workforce tends to transition out of farm work. Figure 10.2b shows the same graph (rescaled) isolating Mexico and the USA. Clearly the USA is further along in the development process. However, Mexico is clearly transitioning out of farm work, too, and it is beginning to import farm workers from Central America (Martin & Taylor, 2013; Taylor & Charlton, 2019).

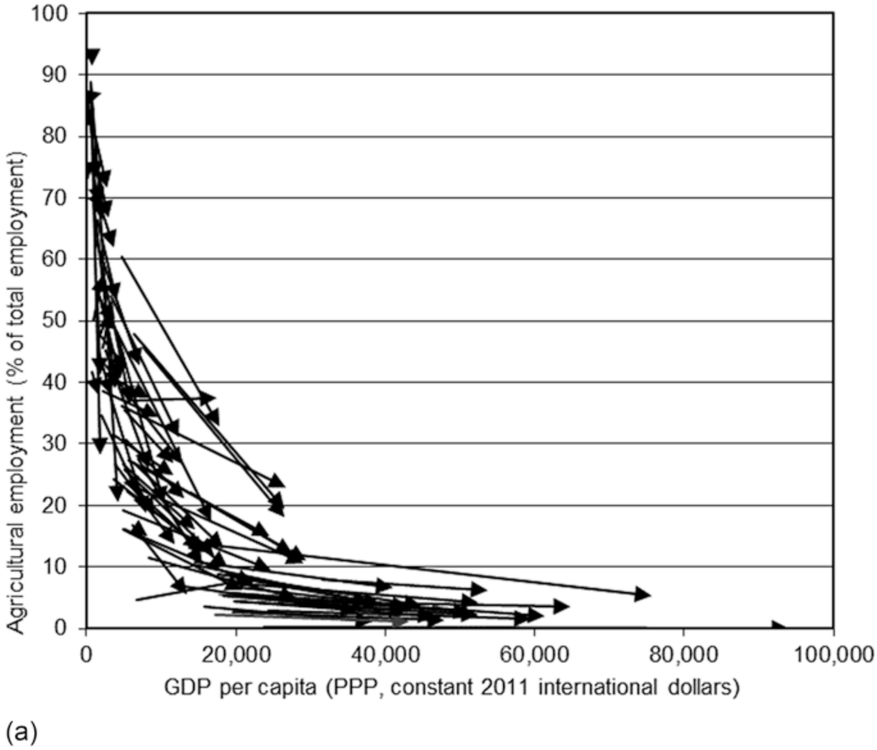
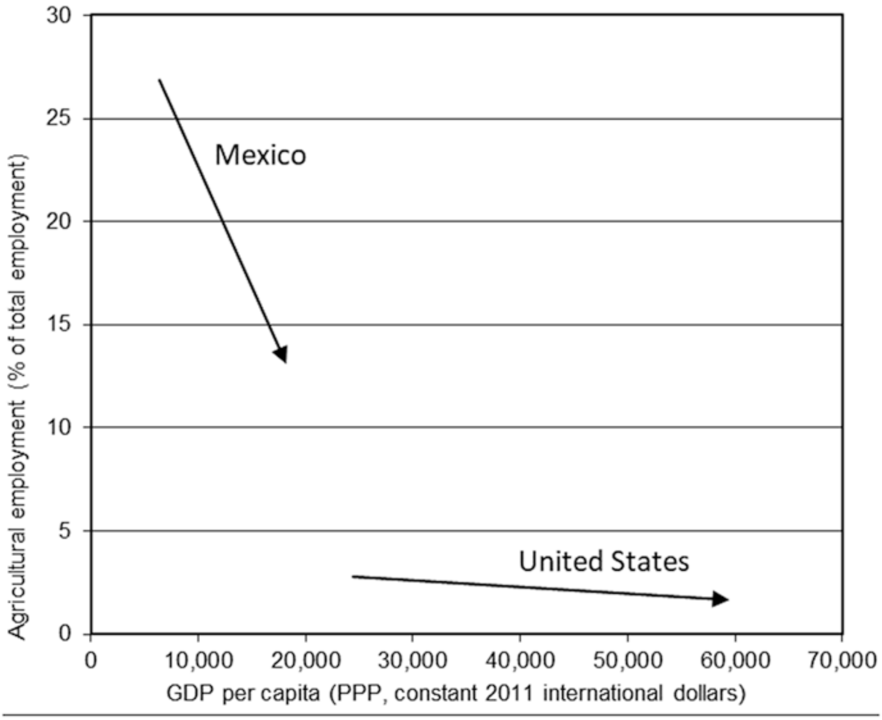


Fig. 10.2 Percentage of individual countries' workforce in agriculture vs. GDP per capita. (**a**) Worldwide. (**b**) Mexico and the U.S.
Note: Constructed by authors using data obtained from the World Bank at https://data.worldbank.org



(b)

Fig. 10.2 (continued)

This process has been examined by two studies that explore the trend in farm work among rural Mexicans (the primary source of labor to US farms). Using panel data from the Mexico National Rural Household Survey (Spanish acronym ENHRUM), Taylor et al. (2012) found evidence that a negative trend in the supply of rural Mexican labor to US farms has been underway for years. In a follow-up study using a more recent version of the ENHRUM data, Charlton and Taylor (2016) quantify the negative trend in the farm labor supply from Mexico and conclude that lower fertility rates, increased educational attainment, and an expanding non-farm economy in Mexico have contributed to a decline in the pool of workers willing to work on US farms.

There is also evidence from the US side of the border suggesting that farm workers are leaving farm work for other sectors of the economy. A 2009 congressional report explains that some farm workers want more stable employment than what is offered by farmers, leading to a search for non-farm jobs (Levine, 2009). A Pew Research Center report finds that there were only two occupations where unauthorized immigrant workers outnumbered lawful immigrant workers (farm work and construction), indicating that the construction sector may serve as viable employment option for farm workers who want to get out of farm work (Pew Research Center, 2016).

Card and Lewis (2007) find that there has been a shift in Latin American employment away from farm work into construction and retail. And data from the National Agricultural Workers Survey (Department of Labor, 2018) reveal that there has been an upward trend in the share of California farm workers who have recently engaged in non-farm work in the USA (Rutledge & Taylor, 2019b).[2] Taken together, this body of evidence points to a US farm labor supply that is shifting inward, where fewer and fewer workers are going into the farm labor force and more and more workers are leaving it. This trend could be problematic for tree fruit farmers and vineyard owners if they are unable to adapt to the new reality that fewer and fewer Mexican farm workers are going to be available in the future.

10.4 Farmer Responses to a Diminishing Farm Labor Supply

Economic theory provides a framework from which we can gain understanding about how decreases in the farm labor supply affect employment and wages in the farm labor market. The theory of supply and demand suggests that a decreasing farm labor supply should lead to fewer workers employed and higher wages. This scenario best describes the US farm labor market over the past two or three decades. Other countries that have experienced a sharp drop in the number of agricultural workers in recent decades include Japan, France, Spain, South Korea, and the UK (Roser, 2020). Figure 10.3 shows the inverse relationship between the number of hired US farm workers and real (i.e., inflation-adjusted) farm worker wages since 1976, revealing a pattern that is consistent with what economists would expect.

In addition to putting upward pressure on wages, farm worker scarcity has caused farmers to make adjustments to their labor management and production practices. Farmers growing labor-intensive crops are most vulnerable to changes in agricultural wages and labor availability. In some cases, farmers have switched from producing crops that must be harvested by hand to others that can be mechanically harvested in order to reduce the cost of labor and remove the risk of not being able to find enough workers during harvest time.

Others have turned to farm labor contractors and the H-2A agricultural guestworker visa program to ensure that they have access to the workers they need when they need them. Nationwide, the number of H-2A visa workers employed in the USA has more than tripled over the past decade, comprising roughly 10 percent of average annual employment in the agricultural sector (see Fig. 10.4; Martin & Rutledge, 2022). However, H-2A visa employment has lagged behind in California, in part because farmers who hire foreign workers through the H-2A program must provide housing, and housing costs in California have skyrocketed in recent years making the program less feasible from a cost-benefit standpoint.

[2] The National Agricultural Workers Survey (NAWS) is a nationally representative annual survey of crop farm workers that is administered by the US Department of Labor.

Fig. 10.3 Hired US farm worker employment and real farm worker wages (1976–2010)
Note: Hired farm worker data were obtained from the National Agricultural Statistics Service (https://quickstats.nass.usda.gov/) and include farm workers directly hired by farmers and farm workers hired through agricultural service contractors. Farm worker wage data were obtained from the Community Population Survey (https://ipums.org/) and are in real (i.e., inflation-adjusted) $2017

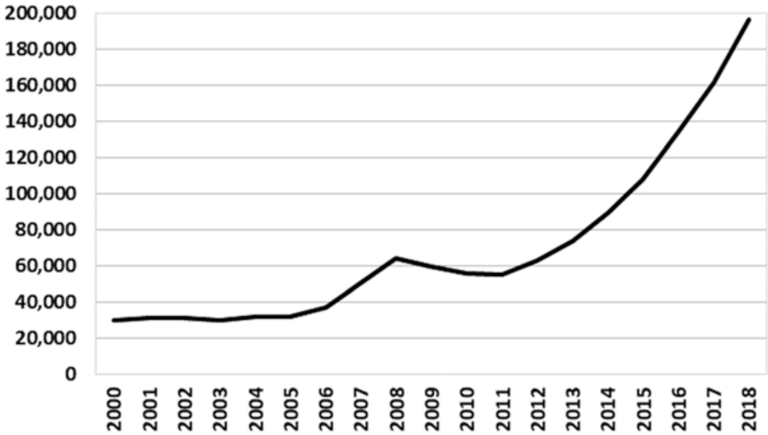


Fig. 10.4 Number of H-2A visas issued (2000–2018)
Note: Visa data were obtained from US Department of State – Bureau of Consular Affairs – and can be found at https://travel.state.gov/content/travel/en/legal/visa-law0/visa-statistics.html

After the passage of IRCA in 1986, researchers uncovered an upward trend in the share of the farm labor force employed through farm labor contractors (FLCs).[3] This trend emerged, in part, because of new laws that made it illegal for farmers to

[3] Farm labor contractors are employers who enter into contracts with farmers to provide certain services, such as pruning, weeding, and harvesting.

knowingly hire undocumented workers (Thilmany & Martin, 1995; Thilmany, 1996). When a farmer hires an FLC to bring workers to her farm, the FLC becomes the official employer of record, which from the farmer's standpoint reduces the risk of legal repercussions from the presence of undocumented workers on the farm. However, recent research reveals that farmers are becoming increasingly reliant upon FLCs to ensure they have enough workers, demonstrating that the motive for employing FLCs has shifted toward finding workers in recent years (Rutledge & Taylor, 2019a).

In response to rising wages and labor availability problems, farmers also report having to make changes to their usual cultivation practices. According to a 2019 survey of over 1000 California farmers conducted by the University of California, Davis and the California Farm Bureau Federation, an increasing share of farmers have had to reduce or delay pruning and weeding, and a nontrivial proportion reported an inability to harvest all of the fruit that was available in their orchards and vineyards (Rutledge et al., 2019; Rutledge & Taylor, 2019a).[4] These changes have been accompanied by increased adoption of labor-saving technologies, such as mechanical harvesters, specialized tractor attachments, automated weeding and irrigation technologies, and handheld power tools. When asked the reason for using a labor-saving technology, the vast majority of survey respondents reported using it, in part, because of rising labor costs. Most of them also cited labor availability as a factor (see Fig. 10.5).

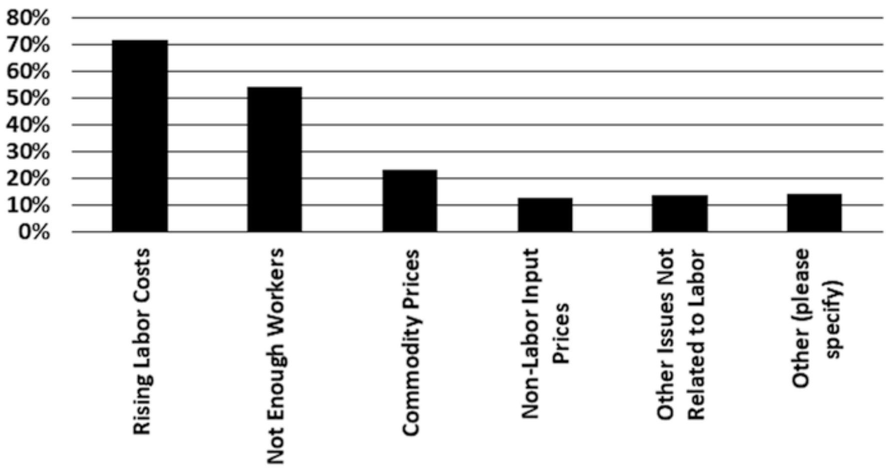


Fig. 10.5 Reasons for labor-saving technology adoption
Note: Results are from authors' calculation of the UC Davis-California Farm Bureau Federation "Adapting to Farm Labor Scarcity Survey" data. Percentages add up to more than 100% because farmers were allowed to select more than one reason

[4] The survey collected information on farmers spanning a period of 5 years between January 1, 2014, and December 31, 2018.

The decision to adopt a labor-saving technology in response to a shrinking labor force can be modeled as a cost minimization problem. It is common to model technology adoption in a two-dimensional framework such as the one portrayed in Fig. 10.6. For simplicity, we only consider two inputs in the production process: capital and labor. Capital inputs include land, buildings, and machinery, and for the sake of parsimony, we assume that the farmer owns a fixed amount of land and buildings so that the only production decision she makes is with regard to how much machinery and labor she will use to produce a certain amount of an agricultural commodity per acre while minimizing her production costs. Figure 10.6a depicts the optimal input mix for a farmer who uses a labor-intensive production process in a labor-abundant environment. The curve denoted $\boldsymbol{Q^0}$ is called an isoquant and represents all the combinations of capital machinery (denoted by $\boldsymbol{K}$) and labor (denoted by $\boldsymbol{L}$) that can be used to produce a given amount of the commodity per acre (say 10 tons of Cabernet Sauvignon wine grapes). The downward-sloping straight lines in the graph are called isocost lines, and they represent all the combinations of capital and labor that generate the same amount of cost at a market clearing wage ($\boldsymbol{w}$) and cost of using capital ($\boldsymbol{r}$). The equation of this isocost line is:

$$\boldsymbol{C = rK + wL}, \tag{10.1}$$

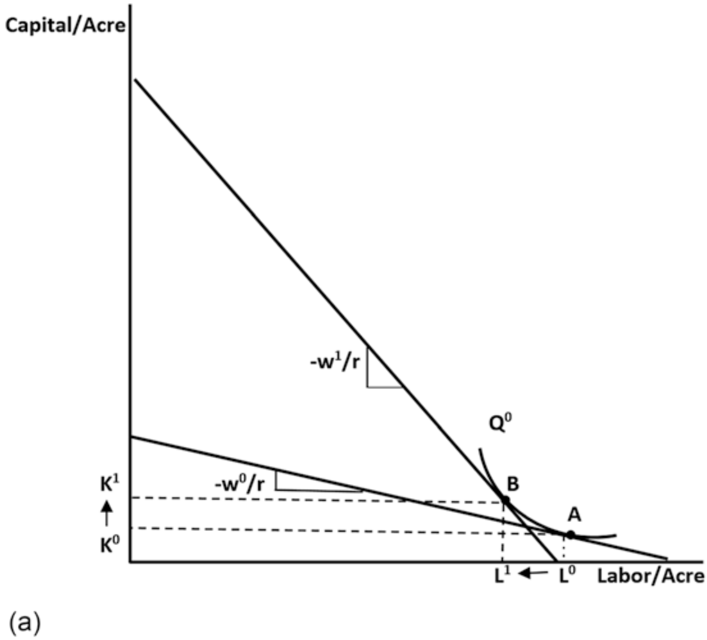


Fig. 10.6 An economic model of labor-saving technology adoption. (**a**) Change in optimal input use due to a change from labor abundance to labor scarcity while using a labor-intensive technology. (**b**) Change in optimal input use due to a switch from labor-intensive technology to labor-saving technology in a labor-scarce environment

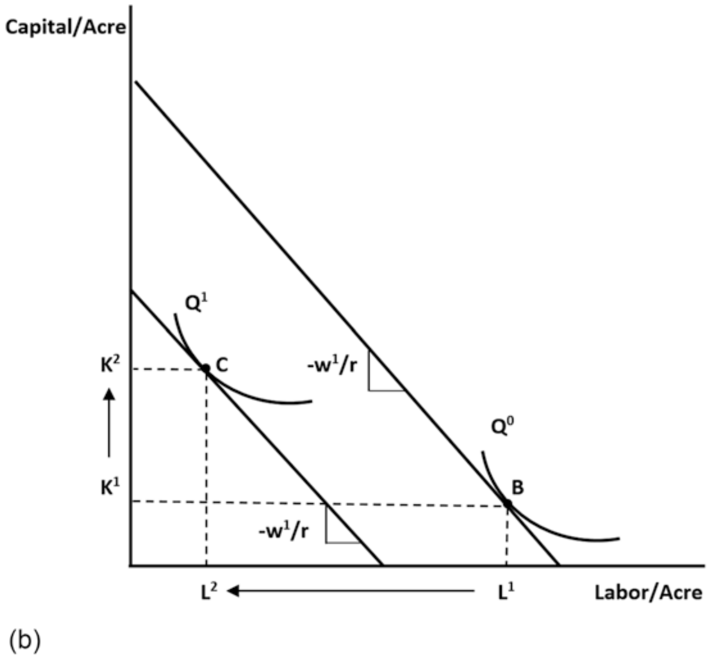


Fig. 10.6 (continued)

where ***C*** denotes the total cost per acre to use ***K*** units of capital and ***L*** units of labor. Rearranging this isocost equation into its point-slope form reveals the following equation:

$$\boldsymbol{K} = \boldsymbol{C} / \boldsymbol{r} - (\boldsymbol{w} / \boldsymbol{r}) \times \boldsymbol{L}. \tag{10.2}$$

Therefore, the slope of the isocost line when labor is abundant (i.e., when the wage $\boldsymbol{w} = \boldsymbol{w}^0$) in Fig. 10.6a is $-\boldsymbol{w}^0/\boldsymbol{r}$. If the farmer wants to produce 10 tons of Cabernet Sauvignon wine grapes per acre in the labor-abundant environment, she will minimize her production costs by using the combination of capital and labor that corresponds to point **A** on the graph. At point **A**, the isocost line is just tangent to the isoquant curve $\boldsymbol{Q}^0$. Thus, her cost-minimizing input mix includes the use of $\boldsymbol{K}^0$ units of capital and $\boldsymbol{L}^0$ units of labor per acre of land.

In a labor-scarce environment, the market clearing wage (i.e., when $\boldsymbol{w} = \boldsymbol{w}^1$) is likely to be higher than it is when labor is abundant (i.e., $\boldsymbol{w}^1 > \mathbf{w}^0$), and the resulting isocost line will be steeper with a slope of $-\boldsymbol{w}^1/\boldsymbol{r}$ such as the one depicted in Fig. 10.6a. In this labor-scarce environment, if the farmer continues to use a labor-intensive production technology, the cost-minimizing input mix will occur at point **B**. Because labor is relatively more expensive in a labor-scarce environment, the cost-minimizing solution requires more capital ($\boldsymbol{K}^1$) and less labor ($\boldsymbol{L}^1$) than it did in a labor-abundant environment.

The farmer may want to consider automating all or part of the production process (e.g., by purchasing and using a pre-pruner or mechanical harvester), which would substantially reduce the amount of labor required. If the farmer chooses to automate part of her production process, her production technology will change, so it can be represented by an entirely new isoquant such as the one denoted by $\boldsymbol{Q^1}$ in Fig. 10.6b. The cost-minimizing input mix used to produce 10 tons of Cabernet Sauvignon wine grapes per acre in a labor-scarce environment using a labor-saving technology occurs at point $\boldsymbol{C}$, where the farmer uses $\boldsymbol{K^2}$ units of capital and $\boldsymbol{L^2}$ units of labor. Note that the new isocost line associated with $\boldsymbol{w^1}$ in Fig. 10.6b has the same slope as the one shown in Fig. 10.6a, but it is closer to the origin of the graph, indicating that the total cost of employing capital and labor is lower than it was when using the labor- intensive production technology. The lower total costs here result from a large reduction in labor costs in a relatively high wage environment. However, the farmer must also factor in the per-period (annual) cost of the loan associated with purchasing the automated technology, so she will only adopt it if the annual cost of capital and labor plus the amount of the loan payment is less than the cost of producing under the labor-intensive technology. As a result, the decision to adopt the automated technology becomes a cost-benefit problem from the perspective of the farmer.

10.5 Agricultural Technology as a Service

One factor that plays a crucial role in the decision to adopt labor-saving technologies is farm size. As the farm size increases, so does the incentive to adopt new technologies because the loan payment required to purchase the new technology can be spread out over a larger number of acres. This means that the per-acre cost of purchasing the new technology is lower on larger farms, which increases the probability that new technologies will be cost-effective. A corollary to this is that smaller farms may not be able to automate even if they would like to, so they may have to continue operating with labor-intensive production practices despite rising wages (or they may go out of business).

A popular model, particularly among agricultural technology startups, is to sell automation as a service (ATaaS). Besides keeping the technology under the control of the startup rather than selling it to the farmer, this business model helps address the challenge of adopting labor-saving techniques on farms too small to justify a large sunk cost of adoption. In theory, it could induce smaller farms (and perhaps larger ones, as well) to adopt automated production processes, enabling them to operate at a lower cost per acre. It could potentially help smaller farmers stay competitive and profitable in a world where larger farms tend to dominate the landscape. Nations around the world have realized the importance of agricultural technology adoption, and automation services could help fill an important void. In a declaration aimed at getting EU member states to support agricultural technology adoption, the European Agricultural Machinery Association (2019) stated that "Digital technologies [for agricultural production] should be available to farmers and farms of all sizes and may help attract younger generations, which remains one of the main social concerns affecting this sector today." According to a recent research report, the ATaaS market is expected to increase to $2.5 billion globally by the year 2024 (BIS Research, 2019).

According to BIS Research (2019), the most common ATaaS models are the pay-per-use and subscription models. Because the service providers own the equipment, this also alleviates any risk associated with having to repair or replace expensive electric or mechanical components when the machines break down. The key players in this market space include Trimble Inc., Deere & Company, AGCO Corporation, CNH Industrial N.V., Accenture PLC, and several others. Within the ATaaS market, there are two main branches: (i) Software-as-a-Service (SaaS) and (ii) Equipment-as-a-Service (EaaS). The most common services currently offered include data analytics, navigation and positioning, yield monitoring, and soil and crop health management. Some companies, such as Blue River Technologies (which was recently acquired by Deere & Company for over $300 million), are in the process of developing automated weeding and fertilization technologies and hope to provide services to the public in the near future.

Automated service markets have also emerged in less developed countries where smallholder farming is the norm. For example, laser land leveling and mechanical transplanting services have proven to be valuable for small rice farmers in India (Lybbert et al., 2017; Gulati et al., 2019). In China, labor-intensive tasks, such as land preparation and harvesting, are increasingly being conducted by service providers (Yang et al., 2013). And service markets have started to develop in Africa, although their development has lagged behind due to poorly integrated markets (Diao et al., 2019). ATaaS markets could be the key to helping less developed countries boost agricultural productivity growth, which has been sluggish compared to developed countries. A recent study of 11 African countries found that only 18% of agricultural households had access to tractor-powered machinery (Kirui, 2019), and it has been suggested that facilitating the development of rental markets for tractor services could help address this problem (Savastano, 2019).

10.6 Industry and University Responses to a Diminishing Farm Labor Supply

Driven by a perceived demand for labor-saving automation and exploiting major advances in mechanical, computer, and agronomic engineering, the public and private sector are investing heavily in developing labor-saving solutions for difficult-to-automate crops and tasks.

Blue River Technologies is developing machines that use cameras, computers, and artificial intelligence with deep learning algorithms similar to what is used in facial recognition systems to allow farmers to see every plant in the field. These systems can tell farmers what types of weeds are in their fields, as well as where and how many there are while permitting variable herbicide or fertilizer spraying regimes to be applied to each plant. These systems can dramatically reduce the need for workers and are designed to substitute machines and computers for manual labor. They also have the potential to help increase crop yields and cut down on non-labor input costs by minimizing the amount of chemicals used in the production process while applying them with a high degree of precision.

The University of California has also been developing technologies that capture data, which can be used to help inform farmers to produce crops more efficiently. One such project, the Virtual Orchard (or VO), is a technology that generates a three-dimensional model of an orchard using a series of aerial images that can measure the volume, height, size, and spacing of trees in an orchard. This system can be outfitted with near-infrared cameras, and the data collected can be used to direct farmers to areas of their orchard that are water or nutrient deficient, which can help farmers reduce the amount of labor needed to properly inspect orchards during the growing season and can help minimize losses and increase yields (Pourreza, 2018).

In addition to the development of smart technologies, the UC system has also invested resources through its Cooperative Extension Program to gain a better understanding of who is using automated systems and whether they are reliable and cost-effective. One such study has found that labor constraints are a "very important" factor in the decision to use currently available automated technologies (Tourte & Siemens, 2018). However, this study also found that there has been a substantial amount of dissatisfaction with the technologies that are currently available and that farmers are generally not confident that they are reliable enough to adopt at this stage. Nevertheless, as resources such as labor continue to become scarce, the role of research and development to make agricultural production more efficient and sustainable will become increasingly important as farmers have to produce more food to feed a growing population.

The development of agricultural technologies has been evolving into a multinational collaborative effort. For instance, the Israeli company Welaunch has started to set up shop in the USA by placing representatives in US states to collaborate with farmers to address their problems. They take the information they gather in the USA back to Israel to develop and test new technologies on Israeli farms before bringing them to market in the USA (Bedford, 2019). In Europe, digital innovation hubs support the development and commercialization of "agri-food robotics" to achieve environment-friendly and labor-saving technologies (SPARC, 2018). It is likely that developments in automation, and their subsequent adoption, will continue to diffuse globally. As software, mechatronics, and artificial intelligence algorithms become more advanced and capable of adapting to a myriad of new situations, these technologies will eventually be designed to target different regions and settings throughout the world.[5]

[5] A number of media reports and technologies are featured on the farmlabor.ucdavis.edu website.

10.7 Economic Welfare and Automation

When agricultural labor is abundant, automation may be detrimental to agricultural workers and small farmers who cannot afford to invest in new technologies, even if the total benefits to society (e.g., through higher farm profits and lower food prices) are positive. In a labor-rich environment, where the majority of farm workers are not well-educated or technologically skilled, the adoption of automated technology has the potential to displace a large number of workers, many of whom may not have other employment options. Although automation leads to an increase in the demand for labor in the technologically skilled farm labor market, it is not likely to offset the overall decrease in welfare experienced by the large number of farm workers who are displaced from employment in the low-skilled farm labor market. Adoption of the tomato harvester created a large increase in the supply of processing tomatoes, which in turn stimulated the creation of new jobs in downstream food processing plants. The extent to which those non-farm jobs compensated for the loss of employment in the field is unclear.

On the other hand, in the current era of labor scarcity, labor-saving automation is more likely to create benefits for workers and consumers, as well as for agricultural producers and society as a whole. As the labor force transitions into a technologically skilled one, wage gains in a labor-scarce environment have the potential to be much larger for those who can acquire the skills necessary to remain in the workforce. Take for example Fig. 10.7, which portrays the labor market for technologically skilled farm workers with fixed labor demand under labor-abundant (panel A)

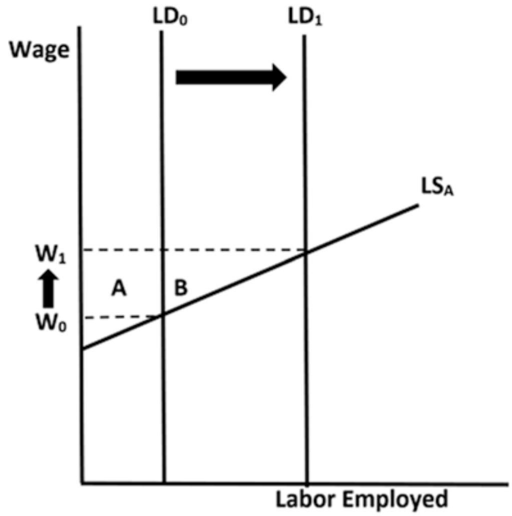


Fig. 10.7 Technologically skilled farm labor market under labor-abundant and labor-scarce environments. (**a**) Labor-abundant environment. (**b**) Labor-scarce environment

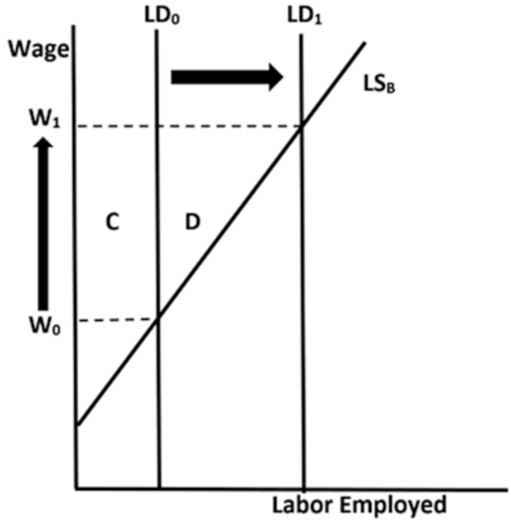


Fig. 10.7 (continued)

and labor-scarce (panel B) environments. This scenario depicts a situation where the automated technology only requires a fixed number of personnel to operate it.

Both of the scenarios depict the same initial wage ($\boldsymbol{w^0}$) and amount of labor supplied at the initial equilibrium. The crucial difference between the two panels is represented by the slope in the labor supply curves (labeled $\boldsymbol{LS_A}$ and $\boldsymbol{LS_B}$). The increase in labor demand for technologically skilled farm workers is represented by the same shift from $\boldsymbol{LD_0}$ to $\boldsymbol{LD_1}$ in both panels. However, the increase in demand for labor in this market leads to dramatically different outcomes under the two scenarios. The market-clearing wage in the labor-scarce environment after the increase in labor demand is much higher than it is in the labor-abundant one, and the gain in farm worker welfare (represented by the area $\boldsymbol{C + D}$) in panel B is much larger than the gain in welfare in panel A (represented by the area $\boldsymbol{A + B}$). In both labor-abundant and labor-scarce environments, the appearance and adoption of new agricultural technologies can lead to a concentration of production on fewer farms. It may not be cost-effective for small farmers to adopt an expensive automated technology because the fixed cost of adoption per unit of output (or land) can be much higher for them than it is for large farmers. If automation leads to increased production or efficiency, prices will decrease, which leads to increased consumption. These changes increase the overall welfare of consumers and the society as a whole, but they can also create winners and losers. Lower commodity prices can drive small farmers out of business, particularly if small farmers lack the scale to benefit from the new technologies.

10.8 Conclusion

A 2018 *Investor's Business Daily* article warned that "Farming robots are about to take over our farms." Extrapolating from current trends in technological development and a diminishing farm labor supply, it is not difficult to imagine a future in which automation in tree fruit orchards and vineyards expands and deepens to encompass more tasks on more farms. Early automation favors tasks for which labor-saving solutions are easiest to develop, as well as commodities for which the delicacy of human hands matters least at harvest time (e.g., fruits to be processed, like wine grapes, versus fruits sold fresh to consumers, like table grapes). However, over time, advances in mechanical engineering and information technology (IT) put automation solutions within the reach of more tasks and commodities. "Robots in the fields" refers to labor-saving solutions that integrate IT with mechanical engineering and other fields, exploiting advances in machine learning and artificial intelligence that enable machines to do things once limited to the domain of humans.

What does a future with robots in the fields portend for farmers, consumers, farm workers, and rural communities?

For farmers, the impact will depend on how new and accessible technological developments keep pace with a declining farm labor supply. If technological development lags, crop production will be more vulnerable to rising wages and declining farm worker availability. Confronted by rising wages and less access to workers, there may be incentives to shift to less labor-intensive crops. If large farms are better able to experiment and become early adopters of new labor-saving technologies, a lag in the development of affordable labor-saving technologies could create challenges for small farmers and accelerate a concentration of crop production on fewer farms.

For consumers, access to fresh fruits and vegetables at an affordable price depends critically on how farmers adapt to a declining farm labor supply. If farmers have access to new labor-saving technologies, they may be able to increase the supply of food to consumers despite rising wages, minimizing food price increases. On the other hand, if these technologies are not available, labor shortages will put upward pressure on food prices for consumers, unless consumers are willing to shift to lower-cost foods, including imports of fresh fruits from countries that find themselves at an earlier stage of the agricultural transformation.

As some farms and crops shift to more sophisticated automation solutions, their labor demands will shift from less-skilled workers to workers who have the skills to work with new technologies. That is, employment will decrease, but human capital demands will rise. Workers who are able to acquire the skills to work with new technologies can benefit from higher wages. Those who are unable to acquire these skills will have to shift to new crops, tasks, or farms that have not yet adopted the new technologies. Societies that succeed in training a new generation of technologically skilled agricultural workers will have an advantage over those that do not. Against a backdrop of declining farm labor supply, it is possible to have rising farm wages (for both skilled and less-skilled workers) and increasing automation. For this scenario to occur, technological change will have to keep pace with, but not outstrip, the negative trend in farm labor supply over time.

In the era of farm labor abundance, the expansion of labor-intensive agriculture created serious economic and social challenges for rural communities in California and elsewhere, as new seasonal farm jobs increased poverty and welfare demands (Martin & Taylor, 2003). Rising farm wages and a shift toward more skilled farm jobs and non-farm employment do the opposite. The impacts of a declining farm labor supply on rural communities, like the impacts on farmers, consumers, and workers, will depend on whether technological solutions keep pace with rising farm wages over time.

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