Eur. J. Hortic. Sci. *81*(2), 78–90 | ISSN 1611-4426 print, 1611-4434 online | http://dx.doi.org/10.17660/eJHS.2016/81.2.2 | © ISHS 2016

Review article

Applications of precision agriculture in horticultural crops

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Summary

Farmer and consumer are driving the request for sustainable production of fruit and vegetables. Precision agriculture, the consideration of spatial and temporal variability for increasing the efficiency of resources, has been developed over the last twenty-five years and was initially applied to field crops. Its application to tree crops and vegetables started later and has been developing with an increasing number of publications as well as research calls in the beginning of the 21st century. First applications were described for mechanical harvesting of horticultural crops with commercial solutions for harvesting fruit that is subjected to processing. A review of methodical approaches and upcoming challenges for precise management of tree crops and vegetables are covered in this paper, addressing horticulturists as well as researchers working in precision agriculture. The precision agriculture domains with specific implications in horticultural crops captured are: data collection, yield mapping, remote sensing, quality mapping, and variable rate application. The spatial and temporal variability in orchards as well as effects of site-specific application of inputs are documented in this paper.

Keywords
arable farming, horticulture, orchard, precision agriculture, precision farming, precision fruticulture, precision horticulture, quality, site-specific management, tree fruits, variable rate applications, vegetables, yield

Significance of this study

What is already known on this subject?

- Obtaining spatial and temporal data have been targeted in the production of fruit and vegetables aimed at characterizing its variability and enable adaptive measures.

What are the new findings?

- Approaches of data collection, yield monitor, remote sensing, quality mapping, and variable rate application are reviewed in the present paper.

What is the expected impact on horticulture?

- The concept of precision agriculture has been applied in horticultural research for 12 years. At the same time information and communication technology has been developed rapidly with the new challenges of big data and agriculture 4.0. The adaptive, precise management in horticultural production is part of it.

Introduction

Precision agriculture (PA) can be defined as management of spatial and temporal variability in fields using information and communications technologies (ICT) (Blackmore et al., 2003). Temporal changes within or between years have been addressed in good agricultural practise (GAP) by means of laboratory analyses of example spots (Srisopaporn et al., 2015), while spatial patterns of plant growth, which have also been known for a long time (e.g., Dale, 1999), have been quantified in large scale with the assistance of PA. PA is, therefore, also referred to as site-specific management. This approach considers a management system for farms that aims to increase yield or sustainability. PA can assist farmers, because it permits precise and optimized use of inputs adapted to the apparent plant status, consequently leading to reduced costs and environmental impact. Because the practise provides record trail, enhanced traceability of farm activities can be obtained that consumers and administration increasingly require (Stafford, 2000; Bellon-Maurel et al., 2014).

PA is a cyclic system. The steps can be divided into data collection and localisation, data analysis, management decisions on applications, evaluation of management decisions; and then a new cycle starts. Each year, data are stored in a database and are used as historical data for future decision-making (Fountas et al., 2006; Gebbers and Adamchuk, 2010). All this large amount of potentially spatio-temporal data gathered using PA applications is leading to the 'big data' concept that will require optimized algorithms to extract the hidden knowledge and relations among variables.

Modern PA has a rather short history. Its application started over the last twenty-five years, when global positioning systems (GPS) and yield monitors were made available in field crops. Harvesting was mechanised and sensors were placed on harvesting machines to measure the spatial distribution of yield continuously. Applications started in cereals using impact or γ-ray grain flow sensors. When first yield monitors were developed and yield maps were created, it was shown that yield and soil properties varied highly within the field. This fact marked the development of modern PA (Hedley, 2015). However, applications in fruit and vegetables

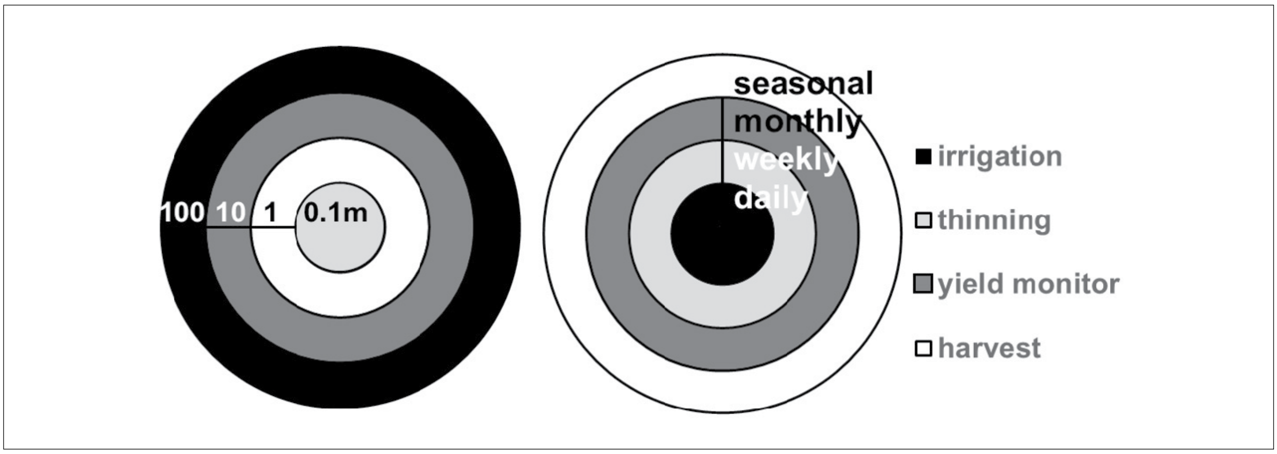

Figure 1. Examples of spatial and temporal resolution of sensor data proposed for specific measures using the concept of precision horticulture.

did not start until the 1990's and were published even later. This delay may be attributed, at least in part, to lack of appropriate technology (Ehsani and Karim, 2010) to record yield or quality data of the crop in an automated way.

PA is frequently referred to as 'site-specific', 'smart', and 'intelligent' farming, while we feel comfortable to use 'adaptive' or 'precise' farming in horticulture. Precision horticulture targets individual trees or zones of tree blocks adaptively to its apparent status that shall trim down environmental footprint of fruit and vegetables production through enhanced resource efficiency and improved production performance. In horticulture, quality analysis of the product is more important than in any other crop. The field size is frequently smaller compared to arable production. The planting density is lower and even single plants may be treated individually adapted to the spatial or temporal pattern. The plant architecture is more complex with planting systems of single rows and missing trees in rows may occur.

Horticultural crops are divided into annual and perennial crops. In the latter, the planting system remains stable over years, while morphological adaptation of canopy and root develops according to the environment. Temporal data over more than one season are important, since historical plant data potentially provide valuable information on the status of endogenous growth factors, e.g., the status of phytohormones and assimilates. Horticultural products are the result of many manual operations and hand harvesting. In perennial fruit trees, even additional production measures are requested, e.g., thinning of flowers and fruits, pruning. In orchards, structures for irrigation, hail net or frost protection are limiting the use of methods for soil mapping, e.g., for electromagnetic measurements, which are disturbed by iron installations (Gebbers et al., 2009).

The present paper aims to give an account to application of PA in mainly fruit trees, but also a few applications published for open-field vegetable crops, capturing specificities, methods used, and results obtained. Viticulture is not captured.

The specificities of the application of PA into horticultural crops in comparison to arable crops are first outlined. The data localization and collection follows, which is crucial and challenging in horticultural crops when various applications are addressed (Figure 1). The next section is about yield mapping, where the majority of fruit and vegetables are handpicked, followed by the applications of remote sensing. Methods for quality mapping are addressed, which is of high interest in horticultural crops due to consumer demands for fresh, appealing produce. The final section is the variable rate application of inputs such as water, fertilizers, and agrochemicals, which is the main outcome of applying PA in crops, where methods and published results are presented.

For this paper, we consider every approach that uses in situ information of plants aiming to manage production of fruit and vegetables more precisely as precision horticulture – no matter if the in situ plant data were obtained spatially or temporarily resolved.

Data collection and localisation

It may depend on the application, if spatial data of the soil are useful to characterise zones or individual trees in the orchard. Correlation between soil and plant data was reported for many fruits, e.g., in apples (Aggelopoulou et al., 2013; Peeters et al., 2015), while a general answer on necessity of spatial soil data in orchard management has not been provided so far and leaves room for future studies. We assume that the irrigation system and temperature gradients as well as crop load and endogenous growth factors influence the apparent plant status to a potentially much higher extent. Alternatively, solely in situ plant data might provide the input for precise management. Plant variables can capture plant growth and development considering entire canopy or down-scaled to leaf, root, flower, and fruit data. Furthermore, physiological processes can be analysed, e.g., leaf gas exchange, xylem sap flow, maximum daily shrinkage of the stem, water potential, xanthophyll cycle, and chlorophyll fluorescence kinetic. Depending on the process a high spatial resolution of the object down to centimetre range might be reasonable, while in other processes a resolution of several decimetre or meter can be appropriate (Figure 1).

The measurement interval needs to be carried out according to the methodology and can be seasonal, weekly, daily, or even the recording of diurnal courses. The plant variable under question, therefore, determines the frequency of data collection. Data collection should be automated, since the amount of data cannot be acquired and processed manually in reasonable time frame for applications (Calfapietra et al., 2015; Hodrius et al., 2015). The choice of feasible sensor platform ranges from satellite, autonomous platform, unmanned aerial system to stationary sensor at the tree.

Analysing the status of canopy as well as yield map-

Table 1. Platforms potentially carrying in situ sensors commercially available for measuring crop properties in orchards on different scales from area down to fruit.

Platform	Sensor	References
Satellite	Infrared, Radar, multi- and hyperspectral cameras.	c.f. Felderhof and Gillieson, 2011; Shahbazi et al., 2014; Nink et al., 2015
Unmanned aerial system	Cameras (colour space, NDVI, IR, stereo), LiDAR, thermal imaging, multi- or hyperspectral reading.	Garcia-Ruiz et al., 2013; Gonzalez-Dugo et al., 2013; Guillen-Climent et al., 2012; Stagakis et al., 2012; Zarco-Tejada et al., 2012, 2014
(Autonomous) tractor	Radar, Lidar, cameras (colour space, NDVI, IR, stereo), ultra sound, thermal imaging, multi- and hyperspectral readings, yield monitor.	Zaman and Salyani, 2004; Wei and Salyani, 2005; Lee and Ehsani, 2009; Bendig, 2015; Rosell Polo et al., 2009; Fukatsu et al., 2014
Crane or slider on frame installation	Cameras (colour space, NDVI, IR, stereo), thermal imaging, multi- and hyperspectral readings, ultra sound, LiDAR.	Park, 2011; Moeller et al., 2007; c.f. Paulus et al., 2014
Stationary logger with cable or radio data transfer – eventually with wireless network	Soil sensors, climate data, balance, acoustic system, cameras, water sensors, dendrometer, optical fruit sensor.	Guo et al., 2015; Anastassiu et al., 2014; Fernandez-Pacheco et al., 2014; Fukatsu et al., 2014; Ampatzidis et al., 2013; Martinez et al., 2013; Verstraeten et al., 2008; Togami et al., 2011; Chang et al., 2011

ping need low temporal resolution and can be carried out on (potentially autonomous) platforms brought to farm on certain occasions (Figure 1; Table 1). In the other extreme, we assume that information on fruit is requested several times during the season to follow its developmental stages. Furthermore, if detailed information on quality of produce are requested, sensor signal should be collected as close to the fruit as possible to avoid perturbation by the environment. Such data acquisition would require high manual workload. Potentially, automated stationary sensors can be implemented that provide time series of fruit data using data logger, data transfer by means of radio eventually using wireless sensor network or mobile network. Performance needs for georeferencing and spatial resolution, here, may be reduced compared to georeferencing in remote sensing and data collection from a moving vehicle. Table 1 demonstrates examples on platforms of sensors.

Summarizing, in orchards several types of data can be collected in situ during the growing season either from micro-climate, soil, tree, and fruit, which all have to be georeferenced using mainly GPS receivers. For most applications such as yield and quality mapping, crop scouting and product sampling, differential GPS (DGPS) with accuracy below 1 m seems to be sufficient (Scharf, 2015). One of the problems encountered in orchards is the limitation for GPS receivers to communicate with as many satellites as possible due to interference by tree canopy. Antennas above tree canopy are used to overcome this problem, which however, is not easy to implement when GPS receivers are mounted on tractors and hail nets are installed. Alternative solutions for data localisation have been introduced in orchards. Taylor et al. (2007) used unique barcodes for specific bays in kiwifruit plantations located in New Zealand. The barcodes were referenced at storage, which also helped to identify spatial quality of fruits. Ampatzidis et al. (2009) used radio-frequency identification (RFID) tags on peach bins, which were referenced in field through portable RFID reader for yield mapping. Tagging of individual trees is used in many experimental orchards meanwhile.

Yield monitor

Spatial information of the yield is pre-requisite for analysis and evaluation in PA as well as in precision horticulture. Yield mapping can be carried out easily in mechanised crops with sensors added to the harvesting machine. In orchards, Rains et al. (2002) introduced a yield monitor for pecan. Pecan was harvested by limb shakers, which caused nuts to fall on the soil. They were collected in the middle of the rows by using blowers for the nuts in the tree rows and sweepers to collect them at the row middle. The windrowed nuts were picked by a chain loader, and after cleaning by blowing air, they were placed on a platform. Load cells measured the load of the platform on the go, while GPS added geo-references to the measurement. The collected material was weighed every second corresponding to 1 m of row. The yield of each tree was defined by nuts collected within 4 m radius of each tree. The same approach may be feasible in apple orchards for experimental purposes, when the fruits will only be used for processing. However, to our best knowledge, no study was published on spatial yield monitoring using a shaker in apple.

Applications in mechanically harvested vegetables have also been presented: Pelletier and Upadhyaya (1999) developed a yield monitor for processed tomato using load cells under the conveying chains of the machine. Hofstee and Molema (2002) presented vision system for potato yield mapping. A colour line scan camera above the conveyor belt captured 2D pictures of the potatoes. Correlation between potato size and weight was established and used for estimation of potato flow in the machine. Yield estimated by the sensor compared to yield weighed on the platforms showed good precision between 3.5 and 4.6%. Yield mapping systems for potatoes based on load cells have shown similar good results of approximately 5% measuring uncertainty (Rawlins et al., 1995).

However, most horticultural crops are not mechanically harvested and therefore many customised approaches for specific horticultural crops have been tested for yield mapping. In Florida citrus plantations, Schueller et al. (1999) used a system to weigh palette bins where oranges were collected. Each worker got picking bags to collect fruits picked

TABLE 2. Yield monitor for handpicked horticultural crops.

Crop	Method of yield mapping	References
Citrus	Weighing pallet bins using load cells from neighbouring trees on tractor platforms. Estimating yield by tree canopy (ultrasonic sensor, Lidar, multi-spectral camera).	Colaço et al., 2015; Das et al., 2015; Peeters et al., 2015; Schuller et al., 1999; Whitney et al., 1999; Ünlü et al., 2014
Apples / Pears / Olives	Weighing bins of handpicked fruits of neighbouring trees, geo-referenced using DGPS.	Aggelopoulou et al., 2011; Fountas et al., 2011; Konopatzki et al., 2015; Vatsanidou et al., 2015
Palm / Plum / Pear / Cranberry	Numbering each tree before harvest and measuring the mass of fruits picked manually. Topographic model or local referencing	Mazloumzadeh et al., 2010; Perry et al., 2010; Pozdnyakova et al., 2005; Käthner and Zude-Sasse, 2015
Peaches / Kiwis	RFID or barcodes on the bins together with a weighing machine, RFID or barcode reader and DGPS.	Ampatzidis et al., 2009; Meena et al., 2015; Taylor et al., 2007
Potatoes	Load cells under the conveying chains. 2-D vision system above the conveying belt.	Hofstee and Molema, 2002; Rawlins et al., 1995
Pecan / Broccoli	Load cells and GPS to weigh the volume and position of the platforms transferring the crop in the field on the go.	Rains et al., 2002; Saldana et al., 2006
Onions / Watermelons	Dividing the field into block and weighing the platforms carrying the fruits per block.	Akdemir et al., 2005; Fountas et al., 2015; Sandri et al., 2014

manually. After filling, bags were emptied in nearby tubs or pallet bins placed between trees (Whitney et al., 1999). Bins were removed by hydraulic lift, which used load cells for weighing, and GPS to record the position of the bin. It was assumed that each bin represented yield of surrounding trees. A reasonable assumption since workers would empty their bags into the nearest bin. Yield was estimated by dividing weight by area covered by each bin. Position and yield were used to prepare yield maps. Spatial variability of yield was observed in a 3.6 ha orange orchard. Results were confirmed in Mediterranean growing regions in grapefruit (Ünlü et al., 2014; Peeters et al., 2015).

For apple orchards, Aggelopoulou et al. (2010) mapped yield, where apples were handpicked and placed in 20-kg plastic bins along rows of spindle-formed trees. Each bin was weighed and geo-referenced using DGPS. The bins, corresponding to 5 or 10 trees, were grouped to represent their yield. The estimation of yield of each tree was not possible due to spindle formation, where branches of adjacent trees were coinciding. The system facilitated workers, who picked fruits continuously, and yield mapping did not interfere with their work. The same procedure for yield mapping was also performed for pears in a small field of less than 1 ha by Vatsanidou et al. (2015).

Fountas et al. (2011) measured yield variation in olive tree orchards. Olives in conventional orchards were picked by hitting fruit branches with sticks. Olives fell on plastic sheets placed underneath each tree. The olives were placed in bags and left in groups where they were filled, for loading on platform. Each bag was weighed and geo-referenced using DGPS. Each group of bags was considered to represent the yield of surrounding trees and was the basis for yield mapping. Spatial variability was observed. Ampatzidis et al. (2009) mapped yield of peaches through RFID tags on the bins. A weighing machine was combined with RFID reader and GPS to record weight and position of each bin. Similarly, Taylor et al. (2007) used barcodes on bins to measure yield in kiwifruits. The data collected was used to produce yield maps of the orchard.

For palm trees, Mazloumzadeh et al. (2010) created yield maps as follows: a few days before harvesting the dates, locations of trees were surveyed and plotted as x-y co-ordinates, fixed at the south-western corner of the grove. Numbers were allocated to all trees located in the grove and, during harvesting, yield of each tree was recorded. In plum, hand-picking was carried out in bins that were transported to the laboratory for single fruit analyses. Spatial pattern of yield and soil ECa was found in an orchard of 180 trees capturing 0.37 ha. Results pointed to low correlation of elevation, soil ECa and generative plant growth (Käthner and Zude-Sasse, 2015). Konopatzki et al. (2015) mapped yield in pear orchard of 5 ha size. They performed selective (n=3) harvests of 36 trees and recorded fruit mass, length and diameter, and soil properties. Results showing high variability of yield with coefficient of variation =77%, and generally low correlations with soil properties. Perry et al. (2010) carried out yield mapping of pears by weighing total fruit mass picked per tree. They found that yield was strongly spatially clustered, suggesting possible management by zones. Pozdnyakova et al. (2005) analysed spatial variability of yield in a cranberry plantation. They used 0.3 x 0.3 m frames to measure the number of fruits before harvesting. Using mean berry mass, they estimated the yield. High spatial variability was also observed here.

Considering hand-picked vegetables, Qarallah et al. (2008) developed an impact type sensor for yield mapping of dry onions. The sensor was used in the laboratory to weigh individual bulbs. Akdemir et al. (2005) have measured the variability of yield in dry onions grown in Turkey. They divided the field into 10 x 10 m grid, collected onions from each grid by hand and weighed them. They found yield variation from 10 to 50 t ha^{-1}. Fountas et al (2015) measured yield of watermelons dividing the field into blocks and measuring yield of each block weighing the platforms carrying watermelons of each block. Saldana et al. (2006) have developed a yield monitoring system for a platform used as a harvesting aid for broccoli. The platform had a weighing system with four load cells which weighed the accumulated product. Yield variation from 1 to 8 t ha^{-1} was observed.

A yield monitor combining harvester and digital camera system was approached in blueberries (Zaman et al., 2008) by counting blue pixels in the images. Aggelopoulou et al. (2011) estimated apple yield by means of digital photography. Zhou et al. (2012) used RGB camera pictures in mid-July, after thinning and after the initiation of colour changing to red, to estimate yield of Gala apples with reasonable success ($r^2 = 0.57$).

Mann et al. (2010) created productivity zones using fruit yield, ultrasonically measured tree canopy volume, NDVI, elevation and apparent electrical conductivity of soil. Citrus fruit yield was positively correlated with canopy volume, NDVI and ECa, but yield was negatively correlated with elevation. Although all the properties were strongly correlated with yield and were able to explain the productivity of the orchard, citrus tree canopy volume was most strongly correlated showing correlation coefficient = 0.85 with yield, explaining 73% of its variation. Tree canopy volume was used to classify the citrus grove productivity into five productivity zones termed as 'very poor', 'poor', 'medium', 'good' and 'very good' zones. Aggelopoulou et al. (2013) have used multivariate analysis for management zones delineation. They used yield, product quality and soil parameters to delineate management zones, but results were contradictory. Assumingly, analysing the spatial pattern of leaf area and crop load (Wünsche et al., 2000) provides a more straightforward approach compared to spatial soil analysis in precision horticulture.

For the studies reviewed, significant spatial variability of yield within the field has been documented in horticultural crops even in fields with less than 1 ha. Temporal variability is an important factor in the development of stable management zones. Research in cereals (Blackmore et al., 2003) and in cotton (Fountas et al., 2004) showed that areas of transient variability are clear after the third year and areas of stable high and low yields and unstable yields can be defined. Tree crops seem to have more stable yields (Fountas et al., 2011), but long-term studies would be needed. Table 2 presents the main horticultural crops subjected to yield mapping, while yield mapping was carried out manually (handpicked).

Remote sensing applications

Remote sensing is a group of techniques that can collect field data without being in contact to the object (plant or soil) using reflectance or emission of light from plant or soil. Light reflectance (sun or artificial) has been used in PA to calculate vegetation indices. The most frequently used vegetation index is the normalised difference vegetation index (NDVI) that is feasible in low-chlorophyll fruits and canopy imaging. Several other indices can be calculated and are in use offering good agreement with leaf chlorophyll measured chemically (Richardson et al., 2002). NDVI is, therefore, correlated to vigour of plants and has strong interaction with yield and sometimes quality. The photochemical reflectance index (PRI) is a normalized difference index using two narrow reflectance bands (531 and 570 nm) that are influenced by the xanthophyll cycle pigment content. PRI is used as stress index providing an effective indicator of, e.g., photo-inhibition and water stress in plants (Weng et al., 2006). Remote sensing using hyper- and multispectral approaches was reviewed recently by Usha and Singh (2013).

Xujun et al. (2007) developed mathematical models to predict yield of citrus trees from their canopy features obtained from airborne hyperspectral imagery recorded in three consecutive years operating nine air missions early in the growing season every year. The models performed well, showing their potential to predict citrus yield several months ahead of the harvesting season. Additionally, Liakos et al. (2011) found correlations between early season NDVI and yield in apples trees for two consecutive years. Suárez et al. (2008) used an aerial hyperspectral camera in olive orchard and found interaction between leaf-level steady-state fluorescence and PRI for the same trees targeting crowns for calculation of vegetation index. For mapping of canopy, steady-state chlorophyll fluorescence has been used for estimating chlorophyll content and water (Ač et al., 2015), while analysing chlorophyll fluorescence kinetic remains challenging in automated measurements. Hsiao et al. (2010) developed dynamic fluorescence index using measurements from a four-channel fluorescence multi-spectral imaging system to estimate water stress conditions of cabbage seedlings.

The measurements of plant reflectance can be carried out by satellites (Panda et al., 2010), airplanes, unmanned aerial systems (UAS), unmanned or manned ground vehicles (Primicerio et al., 2012). Satellites can provide images of large areas, at relatively low cost, but cannot work when clouds are absorbing and scattering the photons. Aerial platforms are less susceptible to potential absorbance by clouds, but are more expensive. Ground sensors work well, but require more labour (Table 2). Ground sensors are frequently using an artificial light that makes measurements independent of sunlight and can be carried out even during night. Canopy and vigour mapping appears particularly challenging in orchards that are trained in vertically with trellising system. Remote sensing (airborne or satellite images) and proximal sensing (images taken within 1 m from canopy) have been extensively used to monitor vigour and canopy in high value crops. In recent years, the use of UAS has also seen high increase (Zhang and Kovacs, 2012), where applications in high value crops start to appear already driven by companies providing semi-commercial solutions.

For estimation of water status, Berni et al. (2009) applied high resolution thermal imagery using UAS for two years to map tree canopy conductance and crop water stress index (CWSI) in olive trees. Additionally, Cohen et al. (2012) used aerial thermal imagery to estimate CWSI in palm trees for two consecutive years in three drip-irrigated plots. They successfully managed to produce a protocol for mapping water status variability that could be used for irrigation scheduling. In vegetables, Clarke (1997) used airborne thermal imagery to detect insufficient irrigation rate, water leaks and malfunctions in subsurface drip-irrigation in muskmelons. These are only three random examples of the application and further developments following Jones (1992). The analysis of plant water status by means of thermal imaging has been reviewed recently (Maes and Steppe, 2012).

Further sensors feasible for remote sensing are light detection and ranging (LiDAR), ultra sound, and texture based image analysis. In citrus orchards in Florida, volume of tree canopy was measured by ultrasonic or laser scanner (Zaman and Salyani, 2004; Zaman et al., 2006). These may be marked as the first publication on precision horticulture and commercial applications have been developed targeting on/off zone spraying meanwhile (Walklate et al., 2002; Mendez et al., 2014). Consequently, remote sensing can be applied for analysing variation of canopy considering spectrophotometric properties and morphology, however, we need proximal measurements to acquire information on the quality of the product.

Quality mapping

Experiments on mapping fruit quality

In horticultural crops, data about spatial variability of product quality should be collected, apart from or along with yield data. Even with the challenges of implementation (Table 1), in situ analyses of fruits have been targeted by many work groups. In high value crops, quality is seen as the crucial factor for marketing. In the past, the Organisation for Economic Co-operation and Development (OECD) set standards considering size, colour, and sometimes shape of the produce. These properties were measurable in sorting lines commercially available since 1992 based on the new vision systems. However, due to unfavourable experiences, mainly with unripe fruit or fruit showing physiological diseases, consumer demands have been increasingly considering internal quality of produce. Regional programmes were established targeting fruit quality and the OECD responded by developing guideline aiming at promoting uniform quality control procedures: "Guidance on Objective Tests for Determining the Ripeness of Fruit" (OECD, 1998). Here, the internal properties of produce are recognized, e.g., sweetness, acidity, fruit flesh firmness, internal browning, glassiness. Coincidently, a new research community working on measuring principles for non-destructive fruit sensing has been established, supported by research funding programmes worldwide.

Early experiments on spatial variability of fruit quality were carried out by means of rating in the field or laboratory analyses. It was expected that plant growth as well as soil parameters may be correlated to fruit quality. However, most papers deal with yield mapping, nutritional and water issues (Agam et al., 2014; Lopez-Granados, 2004; Zaman and Schumann, 2006; Zaman et al., 2006) pointing to huge spatial variability. However studies for quality mapping and the correlation with soil and plant parameters at field scale are still limited. The influence of spatial variability of chemical soil properties on spatial pattern of fruit diameter was analysed in pear grown in continental, temperate climate (Konopatzki et al., 2009). In apple production, it was pointed out that fruit development and soil apparent electrical conductivity (ECa) were well correlated (Türker et al., 2011). Taylor et al. (2007) studied the spatial variability of kiwi fruit quality in eleven orchards in New Zealand and considered implications for sampling and mapping based on fruit quality. They pointed out that fruit weight had more advantages to manage harvesting spatially than dry matter.

Aggelopoulou et al. (2010) analysed spatial variability of quality in apples. They measured several parameters of quality including fruit mass, skin colour, soluble solids content, malic acid content, juice pH, and fruit flesh firmness. They found that areas of high yields had lower quality, which can be explained by high crop load and inadequate leaf area per fruit. The variability of quality was high and spatial pattern varied because of temporal variability over three years of the experiment. In European plum correlation of spatial pattern of soil ECa and generative growth, capturing also fruit size, was found in temperate climate (Käthner and Zude-Sasse, 2015). The between-year variability was low for soil pattern, but high for fruit quality. Consequently, for mapping fruit quality, we can assume that measurements are requested at least every season. For analysing the fruit developmental stages even several measurements per season or continuous monitoring would be beneficial. Crucial is certainly the availability of feasible sensors for automated in situ monitoring.

Quality analysis in situ

For non-destructive analyses of internal quality, sensors are under development or have been commercialized during the past 15 years. It can be expected that still more sensors will become available in the near future. In the field, mechanical impacts on fruit can be measured transferring data by radio or Bluetooth communication protocols (Herold et al., 2001; Praeger et al., 2013). Note that we consider this approach still as precision horticulture as long as readings were carried out in situ to manage the orchard more precisely – even if the spatial resolution is extremely low and only example trees are analysed.

Fruit and stem diameter can be measured with dendrometer, linear displacement position sensor, and shadow imaging. Instruments are available equipped with wireless sensor network. Methodology was reviewed by Fernandez and Cuevas (2010) and systems are applied in commercial orchards already. Optical properties of fruit and vegetables that may be considered in their non-destructive analyses are wavelength-dependent: absorption coefficient, scattering coefficient, anisotropy factor, refractive index, fluorescence, chlorophyll fluorescence kinetic and fluorescence life-time. Methods are commercially available as hyper- or multispectral systems as well as imaging techniques (Table 3).

Applying spectroscopy in the near infrared (NIR) or visible ranges provides information on absorption of water, carbohydrates expressed as soluble solids content (SSC) or pigments, respectively (Olsen et al., 1969). Several portable sensors are available to measure dry matter and SSC by means of NIR spectroscopy (Bellon-Maurel et al., 2010; Cen and He, 2007; Nicolai et al., 2007) and pigments of apple in the visible range (Merzlyak et al., 2003; Zude, 2003; Seifert et al., 2015). Earlier literature approached the determination of optimum harvest date by means of laboratory analyses or the analysis of quality in postharvest using the SSC or pigment contents of fruit. In mango, dry matter and eating quality was used for monitoring fruit developmental stages (Subedi et al., 2007). In the context of precision horticulture, Zude et al. (2008) used localized readings using a hand-held NIR system for spatial harvest management in mandarins recognizing SSC of fruit. When the steady state of SSC was reached, trees were marked as ready-to-harvest in the map of the orchard. Time-resolved as multi-spectral system and spatially resolved backscattering imaging as hyper- or multispectral approach can be applied to obtain information on absorption and scattering coefficients (Cubeddu et al., 2001; Taroni et al., 2003; Lu, 2004; Baranyai and Zude, 2009). These two methods have been evaluated by various workgroups pointing out high potential of the approach for distinguishing fruits grown in zones of drought stress and well-irrigated zones (Qing et al., 2008).

Recording the fluorescence or life-time of fluorescence signal by means of laser-induced fluorescence spectroscopy was introduced for monitoring marker molecules or nutritional important compounds with desktop modules (Wulf et al., 2008). The life-time analysis has been studied rarely, but may address the consumer request for health-promoting products. In viticulture, mapping of the fluorescence signal of fruit has been applied in several studies, which are not included in this paper. Fluorescence-based optical sensors have been successfully implemented apart from grapes quality, also in apples to non-invasively analyse the content of chlorophylls, anthocyanins and flavonols in 'Fuji', 'Granny Smith' and 'Golden Delicious' apple cultivars (Betemps et al., 2012). The chlorophyll fluorescence can be recorded in situ

Table 3. Spectral photometric methods available as portable systems for in situ analysis of fruit. Reviews or recent publications in case no review was found are listed.

Measuring principle	Feature	Reviews or, if not available, recent references
	Frequency domain	
Hyper- and multispectral spectroscopy in the visible range	Anthocyanins, carotenoids, chlorophylls	Merzlyak et al., 2003; c.f. Zude, 2003; Kozukue and Friedman, 2003; Ziosi et al., 2008; Seifert et al., 2015
Near infrared spectroscopy	Dry matter, soluble solids content	Nicolai et al., 2007; Cen and He, 2007; Bellon-Maurel et al., 2010; Abu-Khalaf and Bennedsen, 2004
Hyper- and multispectral imaging	Same as visible or NIR	Pu et al., 2015; Lorente et al., 2012
Photogrammetry	Size, shape, colour, biospeckle	Vijayarekha, 2012; Blasco et al., 2012; Moreda et al., 2012; Zdunek et al., 2014
Fluorescence	Chlorophyll, phenols	Lichtenthaler et al., 2012; Nedbal et al., 2000; De Ell et al., 1998; Kuckenberg et al., 2008; Wulf et al., 2008
	Time domain	
Distribution of time of flight	Anthocyanins, carotenoids, chlorophylls, effective path length	Cubeddu et al., 2001; Taroni et al., 2003; Zude et al., 2011; Kurata et al., 2013; Gobrecht et al., 2015
	Space domain	
Spatially-resolved hyper- and multispectral Imaging	Wavelength-dependent, same as NIR or Vis, scattering properties	Lu, 2004; Peng and Lu, 2006; Baranyai and Zude, 2009; Nguyen et al., 2014

providing information on fruit blush colour and fruit maturity (Kuckenberg et al., 2008). The most prominent system used in practise is for sure the Harvest Watch™ applied in apple monitoring postharvest in storage rooms (De Ell et al., 1998). The analysis of chlorophyll fluorescence kinetic is feasible in precision horticulture, since in situ measurements are enabled with pulse-amplitude-modulated (PAM) method for kinetic analysis in various light conditions. The efficiency of photosystem II and light saturation can be analysed by the PAM chlorophyll fluorescence kinetic, again with the option to measure images of fruit (Nedbal et al., 2000). Many studies are available in stress physiology that point to applications in precision horticulture by mapping spatial variability of fruit properties. Furthermore, Ruiz-Altisent et al. (2010) reviewed advanced sensing technologies that have been used for quality analyses in fresh fruit and vegetables in the laboratory: X-ray fluorescence and MIR for measuring inorganic nutrients, terahertz spectroscopy for detecting monosaccharides and water (Kameoka and Hashimoto, 2009), X-ray or optical coherence tomography that can provide data on cavities and internal structure of the product (Fischer et al., 2008; Mathanker et al., 2013; Matsushima et al., 2013), nuclear magnetic resonance (NMR) imaging for analysing water distribution (Windt and Blumler, 2015). The methods appear still advanced considering the measurement in the field. Handheld systems of Raman spectroscopy for analysing the distribution of nutritional valuable compounds are under development (Maiwald et al., 2015).

Qiao et al. (2005) developed a mobile grading robot for peppers capturing yield and quality data. It was moved to a plant and a worker picked the peppers and placed them on the machine for grading. The machine was equipped with a GPS receiver on it to locate the plant, weighed and analysed the fruits of each plant. Consequently, robots providing spatially resolved data as well as stationary sensors enabling the recording of time series can further support the gain of information from the farm.

Variable Rate applications

Variable Rate (VR) application is the major target for PA. All information gathered should result in adapted management of the defined zones.

In citrus orchards in Florida, tree canopy measured by ultrasonic or laser scanner was correlated to yield. This property was used to vary fertiliser application (Zaman et al., 2005, 2006). In sprayers, sensors can detect missing trees and then stop nozzle output. Additionally this set up automates stopping of sprayer output at headlands and facilitates operator's work. Other sensors sense the trees' density and height using laser scanners, ultrasonic or photoelectric sensors (Giles et al., 1988) and adjust spraying direction of nozzles to reduce out-of-target spraying.

In olive trees, Lopez-Granados et al. (2004) created site-specific fertilization maps based on leaf nutrient spatial variability. They found that consistent saving in N, K and P fertilisers could be achieved if a differential fertilization programme was based on spatial variability of leaf nutrient status of the trees. Fountas et al. (2011) also applied manually to each olive tree P, K and pH based on prescription maps from soil analysis.

In apples, Aggelopoulou et al. (2010) have used soil analysis data and nutrient removal from the soil by the crop to prepare prescription maps for fertilizer application. Farooque et al. (2012) delineated zones for nitrogen fertilization in blueberry by means of soil and fruit yield clustering. Prescription maps may be based on characteristics measured during the growing season. Aggelopoulou et al. (2011) found high correlation between flowers and yield distribution in apple orchards. This information can be used to manage the inputs to the crop as requirements of trees with high crop load are different from trees with low crop load.

VR irrigation is also of importance due to shortage of water reserves and necessity of irrigated crops for food security. Irrigation systems for perennial crops have to be designed from the beginning to achieve VR irrigation. Knowing the soil variability, it is possible to develop more than one network applying different water volume or frequency. Goodwin et al. (2008) have applied VR irrigation in a nectarine orchard. They assumed that water requirements of each tree depended on its canopy, which could be measured by remote sensing. They divided the orchard into rows and applied water based on the larger trees of each row, achieving economy in the range of 1,700 m^3 ha^{-1}. In the NASA Terrestrial Observation & Prediction System (TOPS) project, satellite images were used to assess vine vigour, estimate crop coefficient (Kc) and regulate irrigation (Johnson et al., 2006).

It should be pointed out that in some applications, management decisions to delineate management zones and consequently apply VR applications should be made tree-individual, e.g., in thinning, while in other applications the zone-specific treatment might be reasonable, e.g., in irrigation (Figure 1).

Conclusions

Horticultural crops pose an emerging and challenging sector for precision agriculture technology and management. From most research reported, spatial variability of yield was confirmed even in small fields, where the majority of horticultural crops are grown in contrary to arable crops. Variability of growth factors affecting yield are the rationale of PA, which is by definition the management of variability. Nevertheless, no mainstream technologies or strategies for measuring yield in orchards and vegetable production are yet in place, while this review may inspire new research for other horticultural crops using more automated methods for yield mapping that are needed.

Quality management is one major component in horticultural crops. Methods to estimate fruit status in the production are required. Advanced techniques have been introduced in experimental practice for measurements on the fruit level in situ. Operations supported by means of in situ information on the plant status will be: on/off zone spraying, thinning, irrigation, frost protection, pruning, and harvest. No applications in viticulture were reviewed, but the huge potential has been pointed out earlier. As most fruits are perennial crops, temporal stability is important for establishing permanent blocks or sub-blocks within the fields. However, the temporal stability of quality pattern still needs more studies. Finally, as many horticultural crops are in small fields in the major part of the world, site-specific technologies and strategies should be developed for small fields, which should be economically viable and easy for small farmers to adopt. This, and the huge amount of data obtained, will be major challenges for the application of precision agriculture in horticultural crops.

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Received: Nov. 23, 2015
Accepted: Mar. 6, 2016

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