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Advanced Engineering Systems for Specialty Crops:

A Review of Precision Agriculture for Water, Chemical, and Nutrient Application, and Yield Monitoring

Editors: Shrini Upadhyaya, Ken Giles,
Silvia Haneklaus, and Ewald Schnug

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Landbauforschung Völkenrode, Special Issue 340, 2010

1 Overview

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Spatial variability in yield within a field even when it is uniformly managed has been the driving force in developing the concept of site-specific crop management or precision agriculture. The hope was that if the reasons for the observed spatial variability in yield could be understood in terms of spatial variability in soil and plant characteristics, then it would be feasible to manage inputs such as nutrients, water, and chemicals so that crop production could be maximized, the amount of inputs could be minimized, the quality of product could be enhanced, and/or potential adverse effects of inputs such as chemicals and manure on the environment could be reduced. The advent of technologies such as yield monitors, the global positioning system (GPS), geographic information systems (GIS), remote sensing (RS), and variable rate technology (VRT) have fueled widespread interest in the concept of precision agriculture. Although much of the early development occurred in grain crops because of the availability of commercial grain yield monitors, attempts have been made to apply this concept to specialty crop production. Many challenges remain for successful adoption of precision agriculture practices for both field and specialty crops. The lack of commercial yield monitors for many crops and reliable and inexpensive sensors to gather required information, the cost and complexity of the technology and the virtual nonexistence of scientifically and economically sound decision support systems (DSS) are some of the key hindrances to the adoption of precision farming practices. However, as agriculture enters the information age, site-specific or even plant-specific (particularly in orchard crops) production practices may be the key for enhancing quality and quantity of production, conserving resources, mitigating adverse impacts on the environment, and competing successfully in an increasingly global agricultural economy.

This paper reviews sampling techniques available to estimate soil and plant attributes and their variability, yield monitoring systems to map crop yield, the spatial variability in soil moisture and nutrients and technologies available to address those sources of variability. It concludes with a review of various variable rate application technologies either currently available or under development to manage chemicals, weeds, and diseases.

2 Sampling Techniques for Plants and Soil

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2.1 Introduction

The practical implementation of precision farming requires that the spatial and temporal variability of soils and crops be measured and understood. It is usually insurmountable and expensive to measure everything, but it is also almost always unnecessary to do so. Survey sampling and stereology provide mathematically valid techniques to make reliable inferences about spatial populations based on small samples. Stereology provides a stochastic approach to measurement of geometrical parameters of a given structure such as volume, surface area, curve length, or 'particle'[1] number (Baddeley and Jensen, 2004).

Soil surveys in many countries have traditionally been based on 'purposive sampling' at points or along transects, in which the surveyor chooses sample locations based on knowledge of the survey area with some restriction to ensure a balanced sample. Another approach that has been used in surveys of small, heterogeneous populations has been for the surveyor to inspect the population and select a small sample of 'typical' units that appear to be 'close to the average'. Many soil surveys deliberately exclude areas of a field that are known to be considerably different from the rest of the field and which could produce inaccurate treatment maps such as for variable rate fertilization (Francis and Schepers, 1997). Although under the right conditions such non-probability sampling methods can give useful results, there is no guarantee that a method that works well under one set of circumstances (which can only be determined for a situation in which the results are known) will do so under another (Cochran, 1977). The need for random sampling procedures for soil surveys has been recognized (Roels and Jonker, 1983; Abbitt, 2002).

When strong correlations exist between population parameters of interest and ancillary variables that are more readily measured, then ancillary data can be used to design efficient unbiased protocols for estimation and for prediction by interpolation (Sections 2.3.1.1, 2.3.2, 2.3.5, 2.4). The increasing resolution, availability and affordability of remote sensing images has made it feasible to collect timely information on soil and crop variability by examining multispectral, near infrared or thermal infrared images (Basso et al., 2001; Best and Zamora, 2008). The normalized difference vegetation index (NDVI) (Tucker, 1979) is correlated with canopy vigor, density, and size and with fruit quality (Price, 1992; Carlson and Ripley, 1997; Zaman et al., 2004; Fletcher et al., 2004; Best et al., 2008; Best and Zamora, 2008; Bramley et al., 2003; Lamb et al., 2004). NDVI may indirectly indicate variability of soil parameters causing variability in tree growth (Taylor, 2004; Zaman and Schuman, 2006). Soil color obtained from aerial images can be an indication of organic matter content and other soil properties (Francis and Schepers, 1997; Kerry and Oliver, 2003). Apparent soil electrical conductivity (EC)

[1] Any discrete physical object contained in a 3-D object, e.g. grains or aggregates of soil, cells, fruit, leaves

measured intensely using electromagnetic induction sensors and elevations measured using GPS may be correlated with a number of other soil parameters (Taylor, 2004; Friedman, 2005; Johnson et al., 2005).

Both survey sampling and stereology have many potential errors of methodology into which researchers may easily fall (Baddeley and Jensen, 2004). Statistically valid inferences about the population can be made if: 1) samples are selected randomly[2] with positive (non-zero) probability, and 2) the sample size is sufficiently large to reflect the variability of soil or crop characteristics. Limiting sampling to regions that are readily accessible (e.g. lower branches of a tree to estimate nutrient content for the entire tree) violates the requirement for a non-zero probability and may introduce bias in the estimator unless the variation across the tree branches is spatially homogeneous, see Section 2.2.

2.2 Design-based and model-based approaches

Two approaches to statistical inference from a sample have developed: design-based and model-based (Thompson, 1992).

Design-based approaches provide unbiased estimators of the parameters of interest by using a well defined random selection procedure, and require no statistical model of the structure such as object shape, stationarity or isotropy. Design-based methods are valuable for the study of highly organized, heterogeneous structures.

In model-based approaches the random variation is assumed to arise from intrinsic randomness in the population. The population is regarded as a single realization of a stationary and/or isotropic stochastic process and the estimated mean value of a variable does not depend on the location and shape of the sample windows or probes[3]. It is therefore not necessary to randomize sample locations. Researchers in precision agriculture and soils have mostly relied upon model-based sampling methods. This has sometimes been under the misconception that design-based sampling requires independence of samples (see Bruis and de Gruijter, 1997, and the discussion subsequent to it). A model-based approach is often preferred when our aim is to formulate models describing the spatial arrangement of a population. Models of the population can be of considerable practical advantage when based on knowledge of the natural phenomena (e.g. climate, dynamics of weed populations, predators or disease) influencing the distribution of the population or when models (e.g. regression relations, process based crop models, soil property functions) are available describing a relationship between the variable of interest with an auxiliary variable. Geostatistical interpolation methods (Section 2.4) are model-based. When a statistical model can be assumed for the population, an adaptive sampling strategy is often optimal (Thompson and Seber, 1996) (Section 2.5). Model based approaches are the basis of several variance prediction models used in stereology (Section 2.6).

Model-based designs can be very sensitive to departures from the assumed model and lead to biased estimators (Baddeley and Jensen, 2004). A less precise, yet robust, design-based estimator may then

[2] The term random is used to mean non-deterministic. It does not mean that events must be independently distributed.
[3] The term probes in stereology is defined in Section 2.2.

be preferred. When the assumptions underlying an assumed model are valid, model-based inference can be more precise than design-based inference (e.g. Särndal, 1978).

2.3 Sampling concepts

The concepts reviewed here are taken from survey theory (Cochran, 1977; Thompson, 1992) and from design-based stereology (Baddeley and Jensen, 2004). Consider the study of a finite 'population' of discrete 'units' arbitrarily numbered 1, 2, …, *N*, where the population size *N* may be unknown (depending on the sampling design). Although usually described with respect to discrete elements (e.g. plants, insects), the theories are equally applicable to continuous media (e.g. soil) that are divided up into non-overlapping discrete sub-units. Suppose the population is the collection of all fruit on a group of trees, then the sampling units may be plots, trees, branches, fruit clusters or any other division that is practically convenient. Our aim is to investigate the population by taking a 'random sample' – a randomly selected part of the population – with the goal of drawing conclusions about the population from information observed from the sample. Of particular interest are population totals (e.g. total number of fruit, total canopy surface area), population means (e.g. mean soil nitrogen content, mean weed density, mean fruit size) and the spatial-temporal variation of such quantities (e.g. distribution of fruit size classes, spatial variation of water content).

A uniform random (UR) 'sampling design' is any well defined procedure for selecting a sample in which all elements of the population are given an equal probability of being selected. UR sampling (together with isotropically random direction, i.e. IUR sampling, for length and surface area estimation) guarantees unbiasedness at the level of geometric sampling, but does not guarantee adequate precision. There are many ways to implement UR sampling, including simple random sampling (SR) and systematic random sampling (SUR, Section 2.3.1). Non-uniform designs are also possible, e.g. probability proportional to size (PPS) sampling, and can be very efficient for sampling inhomogeneous or rare populations (Section 2.3.2).

In simple random sampling without replacement (SR-wor), we use a random digit generator or a table of random digits to select a fixed number, *n*, of distinct units with label numbers between 1 and (known) *N*. The sampling probability for each unit is *n*/*N*. Simple random sampling with replacement (SR-wr), which generates independent samples, is generally the most inefficient of sampling designs (followed by SR-wor) but serves as a reference procedure because it is the only design for which the mathematical properties are completely known. Three UR sampling designs for selecting plots from a 'field' are illustrated in Figure 2.1(b)-(d). The Smooth fractionator design (d) is described in Section 2.3.1.1.

A general estimator of the population total, *Q*, may be written (Horvitz and Thompson, 1952) as

$$\hat{Q} = \sum_{i=1}^{n} \frac{q_i}{\pi_i} \tag{2.1}$$

where q_i is the content (the amount of the parameter under study) of unit *i* in the sample, π_i is the positive sampling probability of unit *i*, and *n* is the sample size (number of units). The sampling probabilities need only be known for the sampled units, but they must be known exactly to provide unbiased estimates of the population total. A UR design is a special case of the Horvitz-Thompson

(HT) estimator (2.1) in which the sampling probability is a constant. SR and PPS sampling provide unbiased estimators of the population mean. Multiplying by the sample size provides an unbiased estimator of the population total, $\hat{Q} = n\hat{\bar{q}}$. Systematic sampling and the HT estimator provide unbiased estimators of the population total. The corresponding estimator of the population mean, $\hat{\bar{q}} = \hat{Q}/n$, is generally biased for SUR sampling because the denominator n is a random variable. The bias decreases as n^{-1} (e.g. Cochran, 1977). If the denominator varies little, the bias is negligible.

In stereology several other concepts are introduced: A 'probe' is a geometric entity (3D slice, 2D plane, 1D line, 0D point) used to penetrate and sample an object. A 'test system' is a set of probes used to obtain stereological estimates, e.g. a regular grid of points for estimating 2D area (Figure 2.2). (The classic work of Warren Wilson (1960) and Warren Wilson and Reeve (1959) to estimate LAI and related parameters using linear probes, and the recent studies by Radtke and Bolstad (2001) and Wulfsohn et al. (2010) provide examples of this stereological principle.) The 'containing space' is the space in which the features of interest are entirely contained (the size and extent of the containing space need not be known exactly). A 'reference space', is a well defined object of known or measurable size, compared to which the size of the feature of interest can be expressed (Weibel, 1980). An example is provided by Wulfsohn and Nyengaard (1999). They estimated the total number of root hairs N (the population total) on a plant root system with a total length L (the reference space, estimated using an unbiased procedure as in Wulfsohn et al., 1999) by the product of the mean density of root hairs per unit root length (N_L) and L.

2.3.1 Systematic random sampling

Systematic uniform random sampling often offers an appropriate balance between the estimator precision and the time spent to obtain samples. It is easy to execute without mistakes, and in many situations is more precise than SR for a given sample size. SUR sampling has been shown to be superior to SR sampling for autocorrelated, stationary populations when the spatial correlation function decreases with distance between units (see Cochran, 1977; Cressie, 1993).

In SUR sampling, every m-th unit in the population is chosen where m is the 'sampling period' and the first unit is selected with 'random start'. The random start is obtained by randomly selecting an integer between 1 and m. Each unit of the population appears in the sample with probability ('sampling fraction') 1/m. A SUR sample of plots in a field and a procedure for evenly spacing the plots is presented in Figure 2.1(c). Sampling on the corners of a regular square grid ('grid sampling' or 'lattice design') or, equivalently at fixed intervals along equally spaced parallel transects (e.g. Flatman and Yfantis, 1984; Mulla and Bhatti, 1997), is probably the most commonly used SUR design used in soil and crop surveys. Triangular or hexagonal tessellations of plots have also been advocated for purposes of semivariogram estimation and spatial interpolation. A SUR procedure for sampling of branches on a stem is illustrated in Figure 2.3(a).

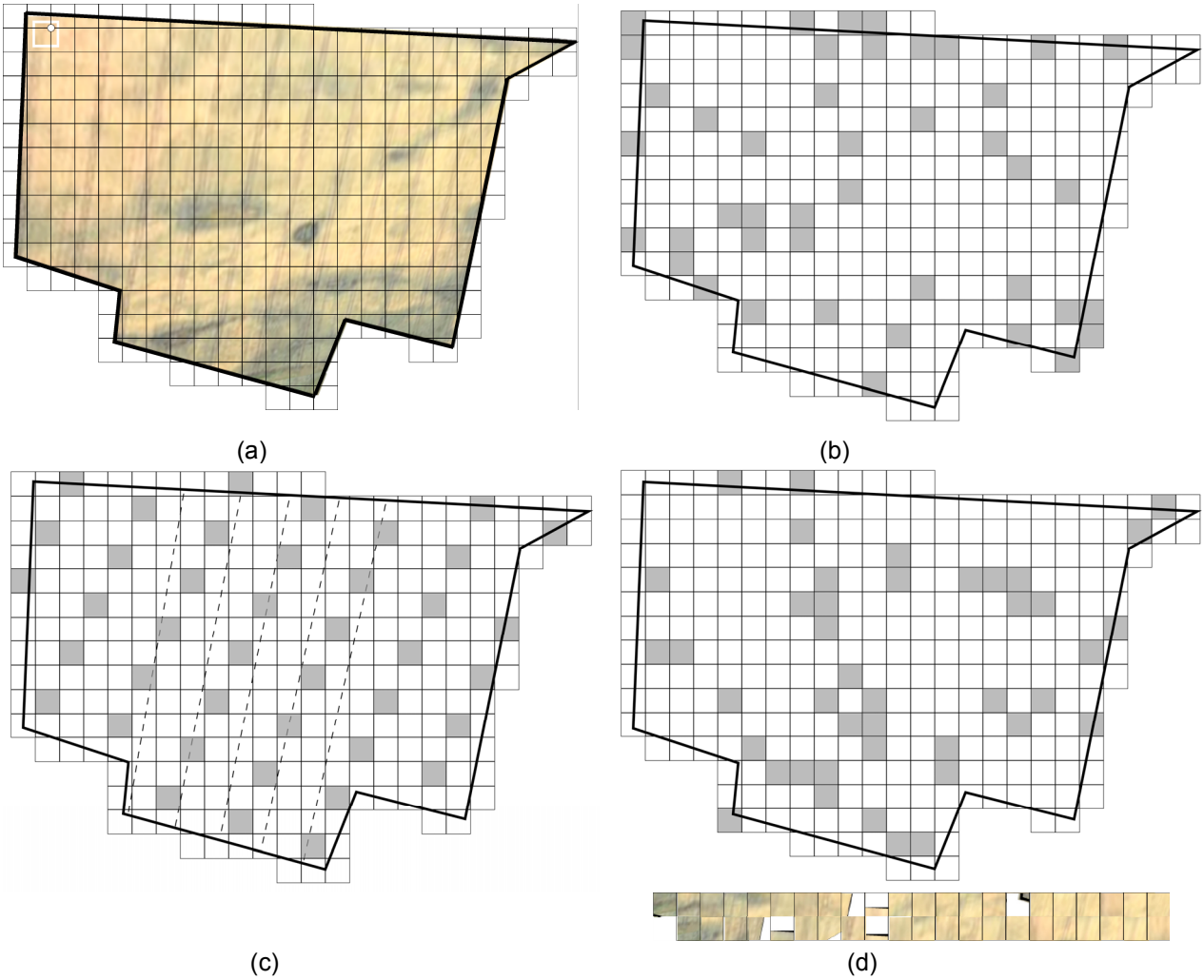


Figure 2.1: Three examples of uniform random (UR) sampling designs for selecting plots in an arbitrarily shaped field, all with the same sampling fraction: (a) A random point is placed within the unit tile (white square), which then defines the UR placement of a tessellation of N = 301 sampling units. The tessellation is of extent to completely contain the field (it defines the containing space). Providing that the tessellation of plots is positioned randomly, then all the following designs provide units (and thereby elements of the population of interest contained within the units) – including edge plots and empty plots – with equal probability. (b) A simple random sample (without replacement) of 43 units. (c) A systematic uniformly random (SUR) sample with sampling fraction 1/m = 1/7 and random start 3 (where the top left quadrat has been designated as unit 1, the quadrat to its right as unit 2, etc.). To avoid aligning samples the position of the selected units is shifted $k = \text{round}(\sqrt{m}) = 3$ units on consecutive rows. When m is exactly divisible by k then the position of the selected unit is shifted k + 1 units on the first consecutive row and by k units on the remaining rows. The combination of sampling unit size and sampling period avoids alignment with tramlines (indicated by dashed lines), a potential cause of periodicity in the soil or crop. (d) SUR sample with 1/m = 1/7 sampling fraction taken from the Smooth arrangement of the units based on mean plot intensity ('smooth fractionator' design). The sampled units are shown in their smooth order (from top left to right, and then bottom right to left) in the strip below the map.

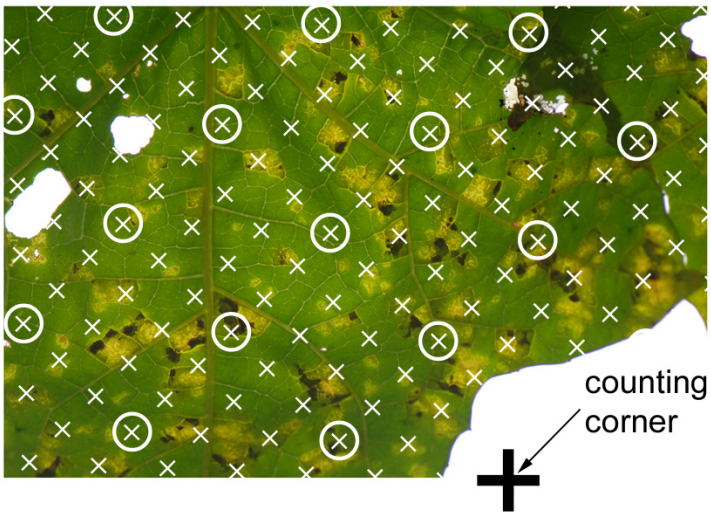


Figure 2.2: Point counting. A (0-dimensional) point is defined as the upper right corner of a cross. The number of intersections, P, between the UR positioned square point grid and the feature of interest is counted. An unbiased estimator of the feature area is given by $\hat{A} = a_p P$, where the grid constant, a_p, is the area associated with a single point. A double grid is illustrated. The fine grid (all points, grid constant a_p cm^2/point) is used to estimate the area of infected (yellow, 9 intersections) and diseased (black, 3 intersections) leaf surface while the coarse grid (circled points, grid constant equal to $9 \cdot a_p$) is used to estimate total surface area (15 intersections). The area fraction of infected+diseased leaf is 12/(15×9) = 0.089 (Photograph of banana leaf courtesy of David Collinge, University of Copenhagen).

Systematic sampling behaves very poorly when a sampling period is chosen that is close to any periodicity in the population variable under study. Management and cultivation effects such as evenly spaced and aligned wheel tracks, trees, irrigation furrows, fertilizing bands, or tillage rows can cause soil or crop conditions to vary systematically (Wollenhaupt et al., 1997; Mulla and McBratney, 2002). The arrangement of branching and axillary flowering structures on parent units of a plant is periodic (phyllotaxy, length of internode). Sequences of patterns may not be clearly evident at some stages of development and scales (Guédon et al., 2001). When visible or known, sampling periods and plot spacing and orientation can be selected so as to not coincide with these periodicities (e.g. Figure 2.1(c)). To avoid sampling units from only one side of a plant stem, leaf sampling periods that are multiples of the phyllotaxic period should be avoided in a systematic design such as shown in Figure 2.3. An approach that has been recommended to reduce errors due to periodicity in the landscape is to take simple randomly positioned samples within systematic random plots, using ‘unaligned sampling’ (Cochran, 1977; Mulla and McBratney, 2002; Webster and Oliver, 2007; Wollenhaupt et al., 1994, 1997) or ‘one-per-stratum’ stratified sampling (Breidt, 1995). Breidt (1995) showed that systematic sampling and one-per-stratum stratified sampling designs are special cases of ‘Markov chain designs’ in which the x and y coordinates of sample points evolve according to Markov chains.

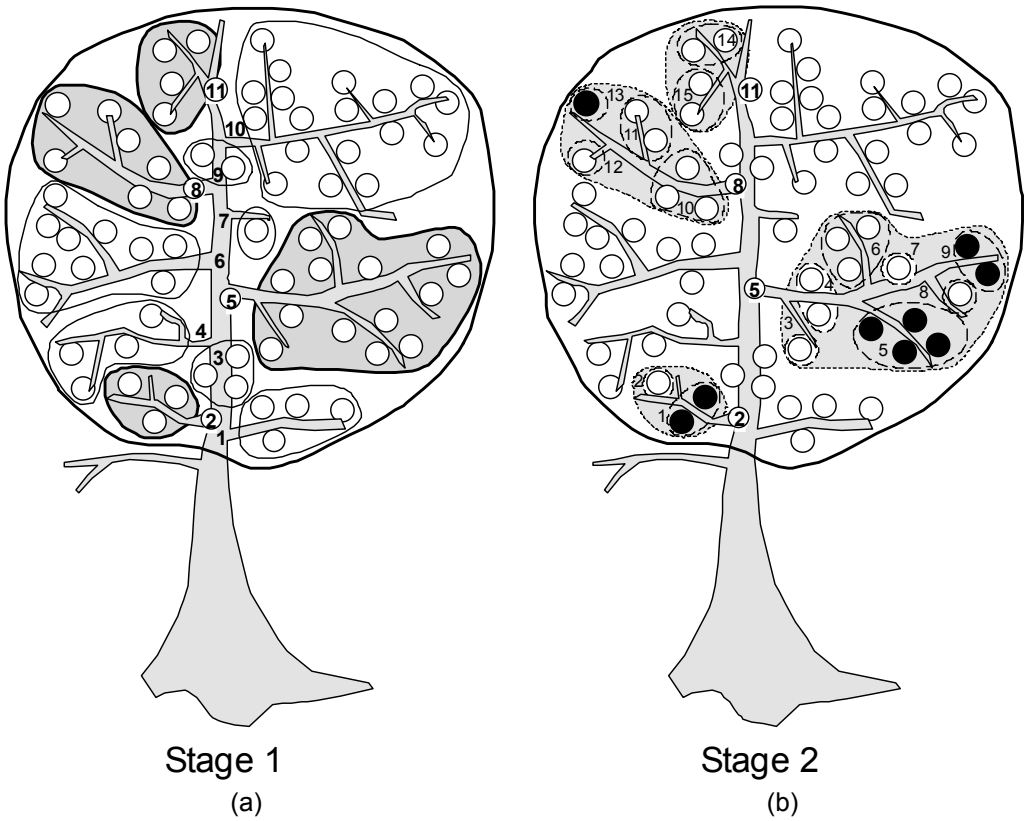


Figure 2.3: A two-stage fractionator sampling design applied to a tree: (a) Primary branches and stem (—) serve as primary sampling units in the first sampling stage, and (b) higher order branches (- - -) are the sampling units in the second stage. Consider sampling the structure with stage 1 sampling fraction $1/m_1$ = 1/3 and stage 2 fraction $1/m_2$ = 1/4, and uniform random starts equal to 2 and 1, respectively. (Stage 1): The first stage sample contains all particles (e.g. fruit) on branches 2, 5, 8 and 11 (circled numbers). (Stage 2): The final sample (filled circles) contains all fruit on branch segments 1, 5, 9 and 13 within the sampled branches. In practice, data is collected as the surveyor steps systematically through the structure: Starting at primary branch 2 we select 2 fruit on branch segment 1. Then step m_2 = 4 branch segments as follows: one remaining segment on branch 2, then jump to branch 5 (2 + m_1 = 5) to segment number 5 where we sample 4 fruit, and so on. Empty units (branches with no fruit) have been ignored. An unbiased estimate of the total number of fruit on the tree is given by the product of the aggregate sampling period m = 12 and the total content of the sample (9 fruit). Figure modified from Maletti and Wulfsohn (2006).

2.3.1.1 Smooth fractionator

The ‘smooth fractionator’ provides a general, straightforward technique to reduce the estimator variance for SUR sampling of heterogeneous populations (Gundersen, 2002; Gardi et al., 2006). It aims to increase estimator precision by increasing within-sample variability and reducing the variability between samples (Gundersen et al., 1999). The procedure is as follows: (1) Conceptually or physically divide up the population into distinct units. (2) Order the units of the population in increasing size. The size here is that of the parameter of interest or that of any quantifiable associated variable (e.g. shape,

texture, spectral intensity, slope, etc.) that is positively correlated with this parameter. (3) Push out every second unit to produce an ordering of the units in a monotonically increasing and then decreasing size. (4) Take a SUR sample of the smooth arrangement. Figure 2.4 shows examples of smooth arrangements of plants and sub-regions of images.

Figure 2.1(d) shows a sample of plots selected using a smooth fractionator with the plot mean red-band intensity (between-plot coefficient of variance, CV = standard deviation/mean = 11%) as the associated variable. (In this example, assume that the parameter of interest is perfectly positively correlated with the intensity.) The coefficient of error (*CE* = *SEM*/mean, where *SEM* = standard error of the mean) due to taking a sample of plots, CE_{plots}, is 1.8% for SR-wr, 1.6% for SR-wor, 3.6% for SURS, and a negligible 0.038% for the Smooth design. Clearly, when surveying sampling locations at the field scale, the ease associated with systematic sampling is lost, an increase in cost which may not justify the gain in precision. The use of GIS and GPS makes smooth fractionator designs more practical.

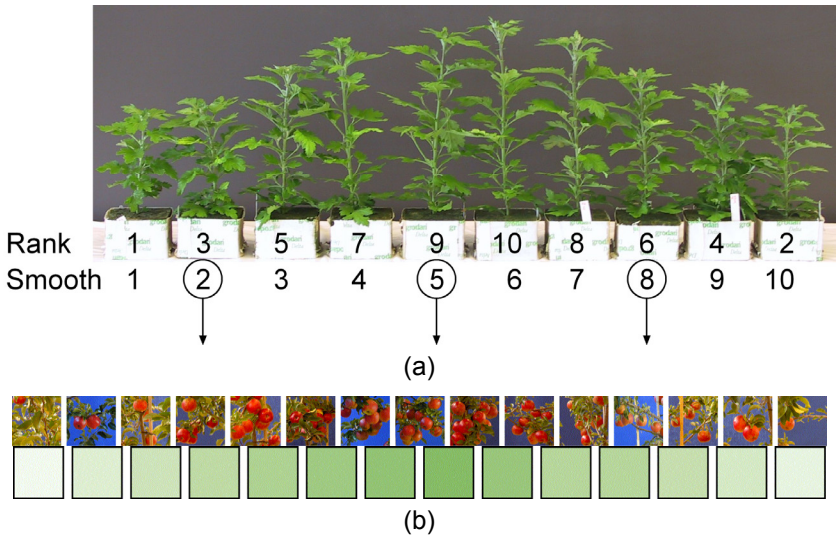


Figure 2.4: The smooth fractionator. (a) A smooth arrangement of plants, using plant height as an indicator of plant surface area for estimating total canopy surface area. 'Rank' indexes plants by increasing height, while 'Smooth' is the labeling of plants according to the smooth height arrangement. In this example a sample of plants is selected with fraction 1/3 with random start 2 from the smooth arrangement. Figure modified from Wulfsohn et al. (2010). (b) A smooth ordering can be implemented based on an auxiliary or associated variable continuously sampled using non-invasive sensors, e.g. the proportion of red pixels in an image window as an associated variable for (red) apple number, or the NDVI value at a location in the field as an indicator of varying crop and soil conditions.

Wulfsohn et al. (2010) examined the efficiency of the smooth fractionator for estimating the total surface area, A_t, of a canopy made up of 50 chrysanthemum plants (between-plant CV(A) = 65%). For a sample size of 10 plants and a precise estimator of leaf area, $CE_{plants}(\hat{A}_t)$ for the Smooth design was 2% when ordering by plant area (Figure 2.4(a)), 10% when using Smooth with three plant height

classes as the associated variable and with plants randomly arranged within height classes before smoothing (introducing a random noise component), and 21% using SR-wor.

2.3.2 Probability Proportional to Size (PPS) sampling

Gardi et al. (2007a) presented a probability proportional to size (PPS) design called the 'proportionator'. Image analysis is used to automatically assign weights to the sampling units, the units are put in a smooth order based on their weights (an optional step), and then a sample of specified size *n* is sampled systematically on the ordinate of the cumulative weight using a sampling period of *Z/n* with random start (Figure 2.5). The probability of sampling a unit is strictly proportional to the recorded weight of the unit and therefore known exactly. An unbiased estimator of the population total is obtained by applying the HT equation (2.1) with $\pi_i = z_i / (Z/n)$, where z_i is the weight of unit *i* and $Z = \sum_{i=1}^{N} z_i$.

Gardi et al. (2007a) compared the performance of SR-wr (i.e., independent sampling), SUR, Smooth fractionator and PPS sampling for estimating the total number of 2500 rectangular 'particles' (of one color intensity but of varying area) and the total and average particle area (using point counting), from a 2D irregularly shaped region divided UR into roughly 400 sampling units. The total intensity of a sampling unit was used as the ancillary variable and weight for Smooth and PPS sampling, respectively. Simulations were carried out for moderately inhomogeneous (between-unit *CV* = 67%), intermediary (*CV* = 155%), clustered (*CV* = 188%) and sparse (*CV* = 293%) particle spatial distributions. Qualitatively and quantitatively the precision of point counting for area estimation was almost identical to that for number estimation. In all cases, SR-wr was the least precise estimator, SURS a few times more precise than SR, Smooth always more precise than SURS, and PPS the most precise except for the homogeneous distribution where Smooth has a slightly smaller *CE*. Increased clustering reduced the precision, with the effect considerably more pronounced for SR and SURS than for Smooth and PPS.

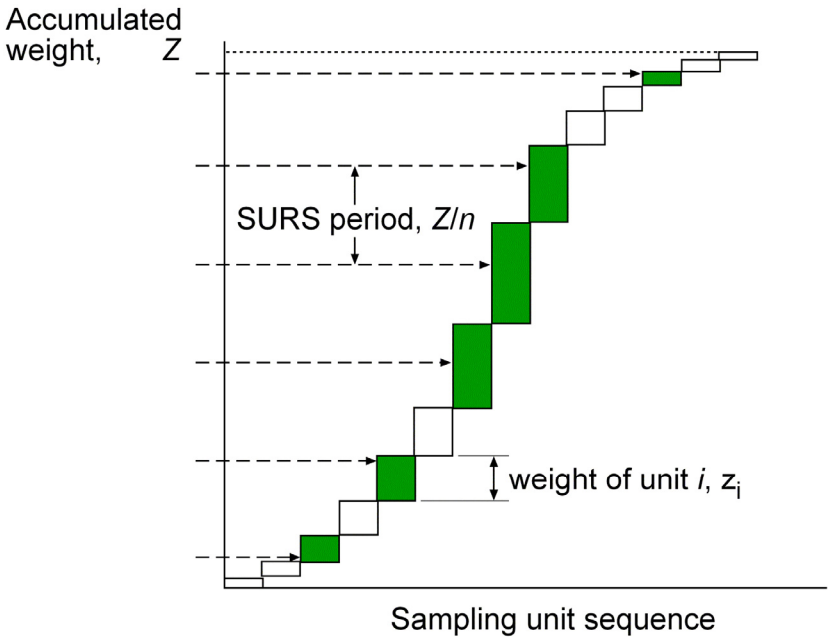


Figure 2.5: Proportionator (PPS) sampling. The complete set of *N* sampling units is listed in arbitrary order or, as illustrated here, arranged in a sequence based on the weights as for the smooth fractionator before SUR sampling. The ordinate shows the accumulated weight. Sampling on the ordinate is systematic with sampling period *Z*/*n* and UR start. The probability of sampling a unit is proportional to the recorded weight of the unit. Sampled units are highlighted (*n* = 6 in this example). Figure based on Gardi et al. (2007a).

Like for the smooth fractionator, the precision of the proportionator is dependent on having a strong positive correlation between weights and counts. Any noise in the relationship between weight and count such as outliers, particles that intersect a sampling unit but are not sampled by the same unit (see Section 2.7), reduces precision.

2.3.4 Multistage designs

A ‘‘level’ is a sampling design in which the measurements are made at a constant scale. There are several reasons for using multilevel (multistage, nested) designs. To obtain a sample of seeds from a vegetable crop, it may be convenient to first take a sample of rows from a field, then a sample of fruit from plots located along the sampled rows, and finally take a sample of seeds from the sampled fruit. One may observe ancillary variables at one scale and make final measurements much more efficiently at a finer resolution. Indices obtained from remote sensing images or soil maps might be used to design stratified (Section 2.3.5), Smooth or PPS designs for field and orchard crops. Basso et al. (2001) used remote sensing to target sampling of soil and crop for input to a crop model and combined remote sensing with model output to identify management zones and to interpret yield maps.

In some cases the variable under study may only be observable at the object scale or under higher magnification. The physical characteristics of weeds are similar to those of crops, complicating the detection of weeds and weed patches in a growing crop (Stafford et al., 1996; Christensen and Heisel, 1998). Thus, weed maps for patch spraying may need to be developed by combining manual and automatic measurements at different scales, such as using aerial imaging (Stafford and Miller, 1993) and vehicle-mounted cameras (Brivot and Marchant, 1995; Christensen et al., 1997) supplemented by georeferenced observations or measurements of attributes (e.g. patch shape and size). Handheld data-logging sampling software can be used to facilitate selection and recording of samples (Stafford et al., 1996; Gardi et al., 2007b).

Multistage SURS designs are called 'fractionator' designs in stereology. Figure 2.3 illustrates a two-stage fractionator for UR sampling of particles (fruit, buds, leaves, spurs, etc.) on a tree. This design is easily applied in practice for a group of trees by treating the union of branches as a single continuous sequence of sampling units (Wulfsohn et al., 2006a). Aggelopoulou et al. (2010) used a two-stage (trees, branches) design to map flowering in an orchard. Data from a SUR sample of 162 apple trees were collected in one day – a sample size adequate for semivariogram estimation and for interpolation. Aravena et al. (2010) used a three-stage design (tree, branch, segment) with systematic sampling of trees and the design illustrated in Figure 2.3 within trees, to estimate total yield in several rows of 14 commercial fruit orchards. Yields at harvest ranged from several thousand bunches for table grapes to over 40,000 fruit for kiwis and apples. Accuracies of better than 5% were obtained in six orchards and between 5-10% in five orchards for workloads of 30-150 minutes, typically less than 90 minutes. Two yield estimates had absolute errors of about 20%. A variance analysis indicated that in one of these orchards a precision of 10% could be obtained for a similar workload by changing the sampling periods for the three stages.

The smooth fractionator is usually applied in a multistage context. Steps 1–4 (Section 2.3.1.1) are repeated as many times as desired to the sampled units obtained in the preceding stage (nesting). Data are collected only at the last stage. The aggregate sampling fraction is given by the product of individual sampling fractions, $1/m = 1/(m_1 \cdot m_2 \cdot \ldots \cdot m_k)$. A nested design leads to dependent observations, which means that inferences can also be made about macro-micro relations if data are recorded at relevant stages.

2.3.5 Cluster sampling

Cluster sampling is particularly convenient for sampling large or complex populations. To conduct cluster sampling, divide the population into a finite number of separate subsets ('clusters') in any fashion that is practically convenient. These clusters are treated as 'primary sampling units'. Then select a random sample (e.g. SR, SUR) of clusters. To uniformly and randomly sample fruit on a tree, take a UR sample of branches. If all clusters have an equal probability of being selected, then each unit in the population has equal probability of appearing in the cluster sample. The fractionator design presented in Figure 2.3 is a two-stage nested systematic cluster sampling design. The primary sampling units are primary branches, while the higher order branches serve as the second stage clusters.

2.3.6 Stratified sampling

Stratified sampling provides a technique for variance reduction. The population is partitioned into non-overlapping subsets ('strata') and each stratum is treated as a separate population for sampling purposes; samples are selected independently from each stratum (e.g. requiring a new random start for each stratum for stratified SURS). Strata can be physical or conceptual. It may be possible to divide an inhomogeneous population into subpopulations (which need not be spatially contiguous), each of which is internally homogeneous. Examples of possible strata are soil horizons, biogeographical areas, morphological zones within plants and management zones based on easily measured ancillary variables such as vegetation indices, yield productivity, soil properties and/or past field history (Basso et al., 2001; Bramley and Hamilton, 2004; Bramley, 2005; Taylor, 2004; Wulfsohn et al., 2006a; Zaman and Schuman, 2006; Sciortino et al., 2008; Best and Zamora, 2008). The benefit of stratification is gained by using different sampling fractions in the different strata (Figure 2.6). Higher sampling fractions could be used in strata which have a comparatively high contribution to the population total to ensure their contributions are estimated more accurately. Very small (but non-zero probability) sampling fractions could be used in areas of a field (delineated as strata) known to be odd and likely to introduce biases when producing management maps for variable rate application. More intensive sampling could be used in strata where variation is large, and sparse sampling applied in strata where properties are more spatially uniform. Seber (2002) reported that large gains in precision can be obtained if the sampling fraction allocated to each stratum is proportional to the square root of the population density in the stratum. Sampling densities for say soil nutrient testing are selected based on prior knowledge of the spatial scale of variability of that nutrient or its mobility through the soil profile (e.g. Francis and Schepers, 1997). McBratney et al. (1999) proposed an iterative procedure for partitioning a field into strata with approximately equal variances based upon intensively sampled correlated ancillary data such as from crop or soil monitors or aerial images. Gallego (2005) described a method to combine stratified, systematic and PPS sampling of satellite images.

Figure 2.6 shows a sampling design in which stratified and cluster sampling have been combined to optimize sampling of fruit from an orchard, the five trees in a cluster would be treated as a continuous sequence of branches for further subsampling as in Wulfsohn et al. (2006a). The purpose of sampling across spatial clusters (blocks) of trees at each sampling location is to reduce the contribution of local variability to the total estimator variance, similar to compositing soil samples obtained from small regions.

2.3.7 Directed or targeted sampling

In sampling programs undertaken for precision farming, an important objective may be to identify areas of a field that are distinctly different from the rest of the field to create variable rate application maps (Mulla, 1993; Francis and Schepers, 1997). A number of studies have used 'directed' or 'targeted' sampling designs, in which sampling is carried out in regions of the field or crop that appear to be visually different from the rest of the field. A frequent motivation is to make accurate prescriptions on the basis of relatively few samples. Christensen et al. (2005) were able to discriminate between N, P and NPK stress in maize plants using visual-NIR reflectance by sampling specific leaf growth stages within a plant, but were not successful when reflectance data for the entire plant were used. Pocknee (2000) showed that directed soil sampling was more effective for characterizing vineyard management

zones. For economic constraints much of the crop and soil property sampling for precision agriculture has been conducted manually on grids with 100 m spacing or more (McBratney et al., 1999; Griffin, 1999). A 100 m regular grid is sometimes excessively coarse to produce accurate prescriptions for site specific soil management (e.g. Brooker et al., 1995, Brooker and Warren, 1997) while in other cases it may be unnecessarily intensive. Griffin (1999) and Mulla and McBratney (2002) advocate targeted sampling as a supplement for a rigorous sampling design, e.g. supplementing samples taken on a regular systematic grid with a few samples taken at locations where there is visible evidence of large changes in the measured property e.g. from aerial photos, electromagnetic induction maps or from patterns in yield maps observed over several years. Bramley (2003) demonstrated that vineyard soil surveys could be improved by using high resolution soil sensing and elevation modeling supplemented by targeted ground-truthing.

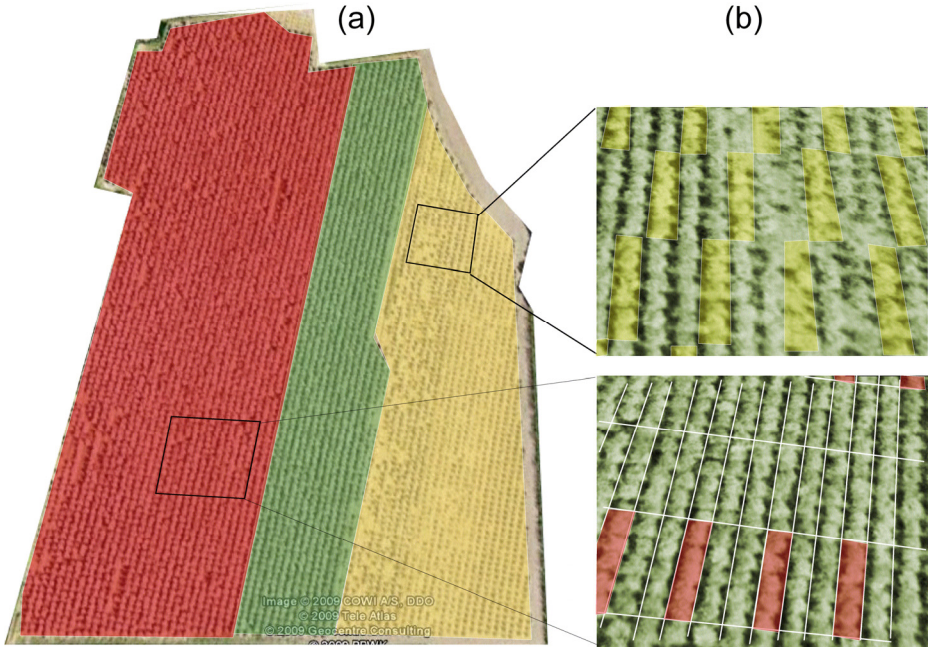


Figure 2.6: A stratified cluster sampling design. (a) Three management zones (the strata) have been identified in an orchard, e.g. based on low, medium and high yielding zones from remote sensing images (highlighted using different colors/tones). (b) In each of the strata, a nested cluster sampling design is applied, with different sampling fractions. The first stage sampling units are blocks of five adjacent trees in a row. In the low yielding (right) zone, a systematic sampling fraction of 1 in 3 sampling units is used with uniform random start. In the high yielding (left) stratum a systematic sample of 1 in 9 sampling units is selected with random start. An intermediate sampling fraction is used in the medium yielding (middle) stratum. Within each of the selected sampling units, a systematic sample of fruit might be obtained using a multistage design such as that shown in Figure 2.3 (perhaps with different sampling fractions in each zone to obtain a desired total sample size in each stratum). The estimator of the population total is the sum of the estimates from the three strata, with proper accounting for the different sampling fractions.

2.4 Geostatistical sampling

The sampling designs presented in the above sections are design-based. The population was considered to be fixed while the sampling design introduced randomness in the sample. When observations are made at sample locations and the objective is to predict values at non-sampled locations (spatial prediction) or to determine parameters of a spatial regression, it is useful to take a model-based approach. The value of the population parameter at location $\boldsymbol{x}$ is now considered to be a random variable z. Given sampled values observed at locations $\mathbf{X} = \{\mathbf{x}_1,...,\mathbf{x}_n\}$, the aim may be to predict the value z_0 at a new location $\boldsymbol{x}_0$. Typically, the values of the variable of interest at nearby nonsampled locations are not independent of each other.

Given accurate measurements at sample locations, kriging provides the interpolation with least bias, and is known as a best linear unbiased predictor (BLUP). Kriging is an exact interpolator, i.e. it reinstates the measurement values at the observation locations. Different types of kriging and geostatistical simulation for interpolation of stationary and non-stationary data have been described in several textbooks [e.g. Matheron, 1963; Journel and Huijbregts, 1978; Isaaks and Srivistava, 1989; Cressie, 1993; Goovaerts, 1997; Lantuéjoul, 2002; Wackernagel, 2003]. A number of studies have compared kriging and non-parameteric interpolaton methods such as inverse distance methods, nearest neighbor, Delauney triangulation and cubic splines (Laslett et al., 1987; Isaaks and Srivistava, 1989; Wollenhaupt et al., 1994; Gotway et al., 1996). When intensive sampling is carried out on a regular grid, kriging, inverse distance, and cubic splines give similar predictions. Kriging is generally superior when the data to be interpolated have a well-developed spatial structure, and are sampled at more than 70-80 points with spacings less than the range of the semivariogram in clusters or at irregular spacings (Laslett et al., 1987; Gotway et al., 1996; Mulla and McBratney, 2002).

There are two primary concerns when sampling for spatial prediction using kriging. One is sampling for parameter estimation. Kriging requires knowledge about the variances of differences between sample locations (the variogram) or the covariances. The second consideration is the placement of samples to minimize variances associated with interpolation. A common dilemma is that geostatistically designed sampling schemes rely upon knowledge of the semivariogram, yet the semivariogram is often unknown until the site is sampled. The sampling needed to determine the semivariogram is often the largest part of the task (Webster and Burgess, 1984) but sampling designs that are efficient for parameter estimation are not necessarily efficient for spatial prediction. A typical compromise is to supplement a systematic grid with some closely related sample locations (Figure 2.7). Diggle and Lophaven (2006) found that supplementing a regular grid with a fixed number k of additional points located uniformly randomly within a small radius of a grid point as in Figure 2.7 yielded more accurate predictions than a regular grid supplemented by more finely filled grids within k randomly chosen cells of the primary grid. Another approach is to use transect designs with points separated by decreasing distances along the transect (Pettitt and McBratney, 1993). Systematically rotated transects positioned on a systematic grid can be used to investigate anisotropy. It may be necessary to conduct a preliminary pilot study to establish the spatial scale. Pettitt and McBratney (1993) reviewed approaches to design and analysis of soil surveys to investigate the spatial variation of an attribute where little of no prior knowledge of the scale of the variation is known. They proposed an approach that was a hybrid of design- and model-based approaches.

Both the total number of samples and the spacing between samples affect the accuracy of an experimental semivariogram (Goovaerts, 1997; Webster and Oliver, 2007). The distance between sample points needs to be just small enough to resolve the scale of variation at the field level. The sampling interval for regular grid sampling programs should be from ¼ to ½ the average semivariogram range of the property of interest to preserve the main patterns of variation (Flatman and Yfantis, 1984).

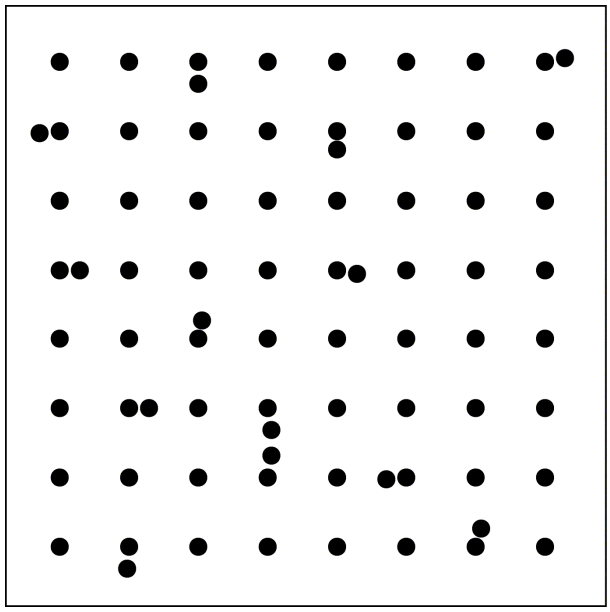


Figure 2.7: Example of a 'lattice plus close pairs' sampling design (Diggle and Lophaven, 2006), aimed at efficient spatial prediction when the variogram is also unknown.

Webster and Oliver (1992) recommend 100 to 150 data locations to obtain a reliable experimental semivariogram for soil attributes using grid sampling and Matheron's method of moments. Where variation is anisotropic even more data may be needed. Kerry and Oliver (2007) found that an adequate model semivariogram for soil properties in four fields in the UK could be obtained using 50 locations at an appropriate distance apart when the residual maximum likelihood (REML) method for semivariogram estimation was used. The REML approach is parametric and the data is assumed to follow a multivariate Gaussian distribution (Patterson and Thompson, 1971; Cressie, 1993; Pardo-Igúzquiza, 1997). The REML method does not yield an experimental semivariogram. Linear combinations of the data celled 'generalized increments' are used to simultaneously filter out the trend and estimate the parameters of the variance-covariance matrix.

When the semivariogram is known, it can be used to evaluate different sampling designs even before samples are collected. One type of analysis is to determine optimal spacing and spatial arrangement of grids for kriging by comparing mean square prediction errors (also called kriging variances). The kriging variance depends only on the semivariogram (or covariance function) and the distances between sampled and unsampled locations, which means it can be computed even when no

measurements have been made at the potential sampling locations. McBratney et al. (1981), McBratney and Webster (1981) and Yfantis et al. (1987) considered the problem of spacing *n* systematic sampling sites on square, triangular and hexagonal grids to achieve an acceptable value of the kriging variance over the region of interest. For a given number of locations per unit area, making observations at the vertices of equilateral triangles minimizes kriging variance. The gain in precision is usually so small that square grids are more commonly used (Webster and Oliver, 2007). Semivariograms of ancillary data can be also used to guide spacing of sampling grids for correlated properties (Kerry and Oliver, 2003). The most efficient placement of grid sampling locations is in the center of each grid cell (Webster and Burgess, 1984).

Kriging variance increases as nugget variance. i.e., the variance due to sampling and measurement noise, increases. Compositing or bulking of soil or biomass samples in small regions or accumulating a sample over a group of plants (treated as a block average) may be used to reduce short-range fluctuations that add to the noise. The aim is to reduce the workload of sampling while retaining some of the precision that comes from having a larger sample size. A model of the semivariogram combined with the kriging equations can be used to determine the optimum number of composite samples to collect at sampling locations (Webster and Burgess, 1984; Oliver et al., 1997). Kriging variances are computed for different combinations of support (size and shape or area) and configurations of sampling locations within the blocks. From these, a combination that meets the tolerance for a given parameter can be selected. In the absence of tolerance limits, Oliver et al. (1997) recommended that for soil nutrient mapping 16 cores be bulked from within a few meters of the sampling location.

Rich data sets may be aggregated into grids of larger cells, where each cell value represents the average of all points contained within the cell, to remove unnecessary small-scale detail. Perez-Quezada et al. (2003) aggregated yield data into 20-m by 20-m cells, using the same mask coverage from year to year, to compare yields for different years in the same locations. Bulking and aggregation of samples involves a ‘change of support’ and values are smoothed. Even where average values are not greatly affected by the smoothing, the observed variability (e.g. as expressed by the *CV*) can be substantially reduced, especially where small-scale variability exists.

2.5 Adaptive sampling

Surveys and mapping of rare, spatially clustered populations such as some weed species and insects or early-onset plant diseases or pests may motivate the use of adaptive sampling designs (Thompson, 1992; Fleischer et al., 1999). Rather than selecting the sample of units prior to the survey, the procedure for selecting sites or units may depend on observed values of the variable of interest during the survey (Thompson, 1992). The goal is to achieve gains in precision or efficiency, compared to conventional designs with similar sample sizes, or to increase the number of elements observed for a given sampling effort. A number of different adaptive sampling strategies exist including ‘sequential sampling’ (Ghosh et al., 1997) and ‘adaptive cluster sampling’ (Thompson and Seber, 1996). Chao and Thompson (2001) considered the problem of optimal selection of new sampling sites to augment a systematic arrangement of sites.

With ‘sequential estimation’ a fixed number of sampling units are collected and the population mean or total is estimated along with a measure of the uncertainty, e.g. confidence interval bounds or the *CE,* under some assumed spatial pattern of the disease or pest. If the predicted uncertainty is within a

desired value sampling ceases, otherwise additional units are added sequentially until the desired uncertainty is obtained. With sequential sampling for classification, sampling ends when sufficient numbers of individuals are collected so that conclusions regarding the population can be drawn with a desired degree of certainty. Sequential sampling designs have been used in a number of studies for pest and disease monitoring in specialty crops (e.g. Allsopp, 1990; Hamilton and Hepworth, 2004; Turechek and Madden, 1999; Gent et al., 2007). Sequential sampling can behave very poorly if the sequential sampling scheme is stopped before the variation in the population is captured because of having sampled similar units or when the population is auto-correlated (Robinson and Hamann, 2008).

In ‘adaptive cluster sampling’ the set of primary sampling units is selected using a probability method, and whenever the observed property of interest in a primary sampling unit meets a given criterion (e.g. weeds are detected in a plot) neighboring sampling units are added to the sample (Figure 2.8). Adaptive cluster sampling will usually provide an improved indication of the spatial extent of the population of interest than non-adaptive designs. The selected sample will generally not provide a design-unbiased estimator of the population mean or total because inclusion probabilities may not be completely known. Thompson (1992) describes design-unbiased estimators of the population mean and total for several adaptive cluster and stratified adaptive cluster designs.

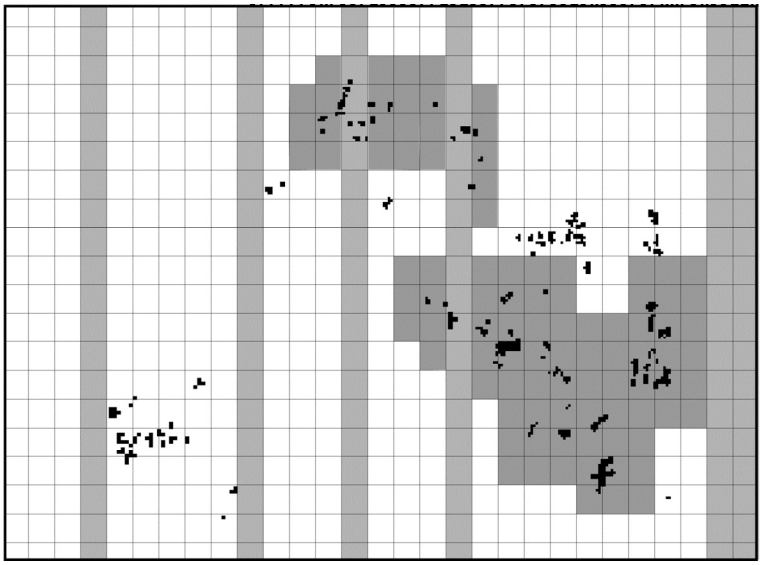


Figure 2.8: An adaptive cluster sampling design with initial SR selection of six strip plots. The final sample is highlighted.

2.6 The accuracy of an estimator

The accuracy of an estimator can be considered the accumulation of two important properties: bias (systematic error, the difference between the expected value of an estimator and the true parameter value) and precision (random error or noise). We can decompose the mean squared error (MSE) into a sum of the bias and variance of the estimator:

$$\mathrm{MSE} = \mathrm{var}(\hat{Q}) + \mathrm{bias}^2(\hat{Q}) \tag{2.2}$$

Both quantities are important and need to be sufficiently small to achieve good estimations. Bias cannot be detected from the data (Mandel, 1964). The much desired property of unbiasedness is a consequence of UR (or IUR) sampling. An important principle in sampling is that variances are governed largely by sample size rather than by the proportion of the population included in the sample, except when sampling small populations (Stuart, 1984; Thompson, 1992). Designing systems to meet requirements for unbiased sampling makes it possible then to achieve a desired precision by controlling sample size.

The total variance (MSE) of an unbiased estimator can be written

$$\mathrm{MSE}(\hat{Q}) = \mathrm{var}(\hat{Q}) = \mathrm{var}(Q) + \mathrm{var}_e(\hat{Q}) \tag{2.3}$$

where $\mathrm{var}(\hat{Q})$ is the total (observed) variance, $\mathrm{var}(Q)$ is the biological (or natural, intrinsic) variance (i.e. the true variability between individuals in the population), and $\mathrm{var}_e(\hat{Q})$ is the sampling error variance. The biological variance is the only meaningful variance for management purposes. Equation 2.3 can also be expressed in terms of the dimensionless squared coefficient of variance (CV = SD/mean, where SD is the standard deviation) and the squared coefficient of error (CE = SEM/mean, where SEM is the standard error of the mean) as

$$\mathrm{CV}^2(\hat{Q}) = \mathrm{CV}^2(Q) + \mathrm{CE}^2(\hat{Q}) \tag{2.4}$$

For a multistage nested design, the total estimator variance can be decomposed into components due to each stage of sampling (Cochran, 1977; Baddeley and Jensen, 2004). Examples are provided by Wulfsohn et al. (2010) and Aravena et al. (2010), respectively, for optimizing estimators of canopy surface area and fruit yield. In many cases it is sufficient to devise sampling schemes so that the contribution of sampling error variance to the total observed variance is small compared to the biological variance. The convention is to aim for $\frac{1}{5}\mathrm{CV}^2 \le \mathrm{CE}^2 \le \frac{1}{2}\mathrm{CV}^2$ to achieve a balance between precision and cost. Gardi et al. (2007b) describe handheld software that can be used to assist in collecting data using multistage stereological designs and obtain estimates of the variance contributions due to each stage of sampling.

The coefficient of error of any estimator $\hat{Q}$ can be calculated based on *k* independent realizations of the estimator $\{\hat{Q}_1, \hat{Q}_2, \ldots, \hat{Q}_k\}$ by applying:

$$\mathrm{CE}^2(\hat{Q}) \approx \left(1 - \frac{1}{K}\right) \frac{1}{(k-1)} \frac{\sum_{i=1}^{k} (\hat{Q}_i - \bar{\hat{Q}})^2}{\left(\bar{\hat{Q}}\right)^2} \tag{2.5}$$

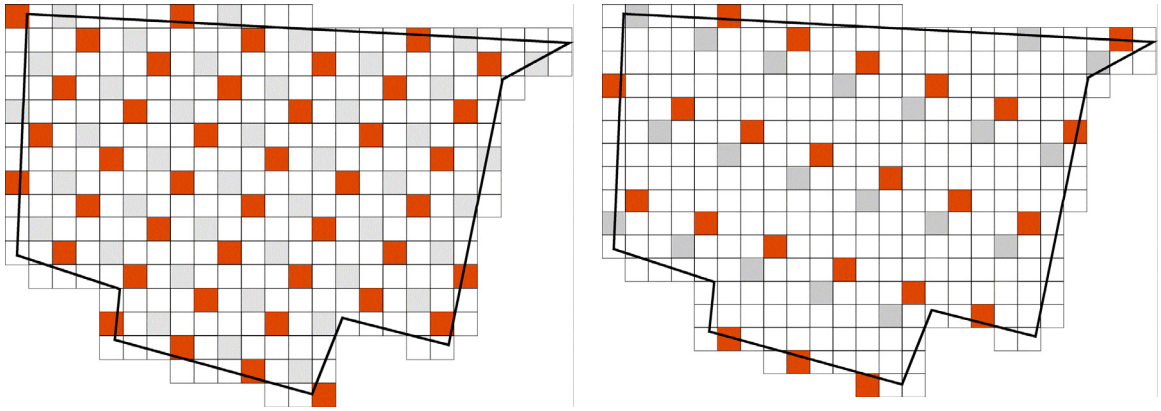
where $\bar{\hat{Q}} = \frac{1}{k}\sum_{i=1}^{k} \hat{Q}_i$ and *K* is the number of all possible realizations of $\hat{Q}$. The variance components of a nested design may be estimated by including independent replication at each level of the sampling

design, e.g. to determine optimal allocation of effort across sampling stages from a pilot study (Baddeley and Jensen, 2004).

A variation of independent repeated sampling to estimate the total variance of any complex, multistage design, is provided by the “random groups” (RG) method (Wolter, 1985). We use *k* repeated samples according to the design (e.g. *k* systematic samples for a SUR design) with repetition applied at the primary sampling stage and the sampling fraction scaled proportionally so as to yield the same final sample size. Figure 2.9 illustrates the difference between repeated sampling with independent replication and the RG method for the design shown in Figure 2.1(c). For the design in Figure 2.3, we may use k = 2 replications at the tree level, repeated for say n = 8 randomly selected trees in an orchard, and compute an average *CE*,

$$CE \approx \left[\frac{1}{n} \sum_{i=1}^{n} \frac{\hat{\mathrm{var}}_e(\hat{Q}_i)}{\hat{Q}_i} \right]^{0.5} \tag{2.6}$$

We distribute the work across trees (which have high biological variability) rather than attempt to obtain precise estimates for individual trees. The RG method is generally biased for SUR for which there is generally dependency between samples. In contrast, an unbiased (but still imprecise) estimate of the CE of the proportionator (Section 2.2.2) can be obtained at no extra cost by taking k = 2 independent samples each of size $n/2$ and applying Eq. 2.5. The estimator of the total now used is the average of the two independent estimates, with only a small loss in precision compared to using a single sample of size n (Gardi et al., 2007a). Aravena et al. (2010) used repeated sub-sampling of *sample data* at each sampling stage and variance decomposition to construct a semi-empirical model for the estimator CE.



(a) (b)

Figure 2.9: Repeated-sampling variance estimation procedures for an SUR design with sample size n and period m = 7, cf. Fig. 2.1(c). An estimate of the population total is obtained by computing the mean of the estimates obtained from the two samples. (a) Resampling with SUR period m = 7 and two independent replicates (random-wr starts 1 and 3). The average total sample size is $2n$. An estimate of the CE is given by Eq. 2.5 with $\hat{Q}_i = \hat{Q}_{m,i} = m\sum_{j=1}^{[n]} q_j$, k = 2 and K = 7. (b) "Random Groups" procedure with k = 2 replicates each with period $k \cdot m$ = 14 (aggregate period m = 7) and random-wor starts 2 and 6, respectively. The average total sample size is n. An estimate of the CE is given by Eq. 2.5 with $\hat{Q}_i = \hat{Q}_{2m,i} = 2m\sum_{j=1}^{[n/2]} q_j$, k = 2 and K = 7.

2.6.1 Predicting the variance of an estimator from a single sample

In practice, resampling procedures can be prohibitively time consuming and methods to estimate variances from single sample are desirable. Devising suitable variance predictors for SUR designs is generally very difficult because the observations of the sample are not independent. Single-sample variance predictors are generally biased, with the degree of bias depending on the extent to which model assumptions are violated for the population under study. Wolter (1985) discusses the performance of large number of variance predictors. The Poisson distribution, according to which CE = $1/\sqrt{n}$ (n is the sample size), provides a model for counting noise and is often assumed as a starting point for a pilot study. Matherons' transitive approach to modeling the covariogram is the basis of several single-sample variance predictors developed for systematic sampling designs in stereology (Matheron, 1971; Cruz-Orive, 1989). Cruz-Orive (1990, 2004) proposed semi-empirical models for predicting the sampling error variance of a fractionator sample. Maletti and Wulfsohn (2006) evaluated the performance of several models and resampling applied to fractionator sampling of trees. Several estimators have been proposed motivated by the problem of estimating the volume of a structure from a systematic sample of area sections (e.g. Matheron, 1971; Gundersen and Jensen, 1987; Cruz-Orive, 1989; Kiêu, 1997, Gundersen et al., 1999; García-Fiñana and Cruz-Orive, 2004). Wulfsohn et al. (2010) showed that similar models could be used to accurately predict variance components of a canopy surface area estimator that combined fractionator sampling of leaves and point counting of leaf area. Point counting (Figure 2.2) using grids of 1.8 and 4.3 cm^2 were found to perform as well as image analysis and a commercial area meter, respectively, for estimating the surface area of a chrysanthemum canopy.

2.7 Sources of bias and unbiased counting rules

The act of sampling a spatial structure by observing it in a bounded window or plot complicates the estimation of geometric characteristics by loss of information due to edge effects. Baddeley (1999) identified two main types of edge effects: 'sampling bias' where the probability of observing an object depends on its size and 'censoring effects' where the full extent of the object to be measured cannot be observed within the window. Sources of non-sampling biases include projection artifacts, operator effects, and biases arising due to difficulties in defining the features of interest.

There are two general approaches to dealing with sampling bias:

(1) The use of unbiased sampling rules, e.g. the 'disector' (Sterio, 1984, Figure 2.10(a)-(b)), the tiling rule (Gundersen, 1978, Fig. 2.10(c)), and the 'associated point rule' (Miles, 1978) (Figure 2.10(d)). These generally require some information from outside the sampling window. We have used the disector counting/sampling rule (a) within a SUR design to estimate the total yield of seed cucumber grown as a row crop in farmer fields, achieving precisions of 10% or better (unpublished report).

(2) The use of weighted sampling methods. Usually these are of the spatial Horvitz-Thomson type, where spatial sampling bias is corrected by weighting each sampled object by the reciprocal of the sampling probability, e.g. the domain can be tessellated with copies of the sampling window and then each sampled object is weighted by the reciprocal of the number of windows that intersect it.

Observation bias due to occlusions of features observed under projection, such as in a 2D image, can be substantial. Wulfsohn et al. (2006b) found occlusion biases in counting of flowers and fruit on small trees of –18% to –31%. In combination with occlusion errors, biases (both positive and negative) can arise because of errors in thresholding and feature recognition. Several studies reporting on algorithms for automatic recognition of apples using 2D images of trees have achieved successful recognition rates from 56% to 100% (typically 85-97%). Rates of false positives were usually less than 5% (Bulanon et al., 2002; Stajnko et al., 2004; Tabb et al., 2006) but could be as high as +15–83% (Stajnko et al., 2004). Bulanon et al. (2002) reported biases of –18% (average of 10 images) under poor lighting conditions. The data of Stajnko et al. (2004) indicate biases of –13% to +21% for averages from thermal images of 20 trees obtained at four development stages.

In some situations there can also be considerable error in recording samples. In surveys of insects in a field it is highly unlikely that every individual will be captured or detected. When carrying out observations of hard-to-detect or rare events such as some weed species or diseases along transects or in plots, the probability of detecting an object depends in some way on its distance from the observer as well as on its size. Thompson (1992) presents methods for estimating and modeling detectability, i.e., the probability that an object in a selected sampling unit is observed.

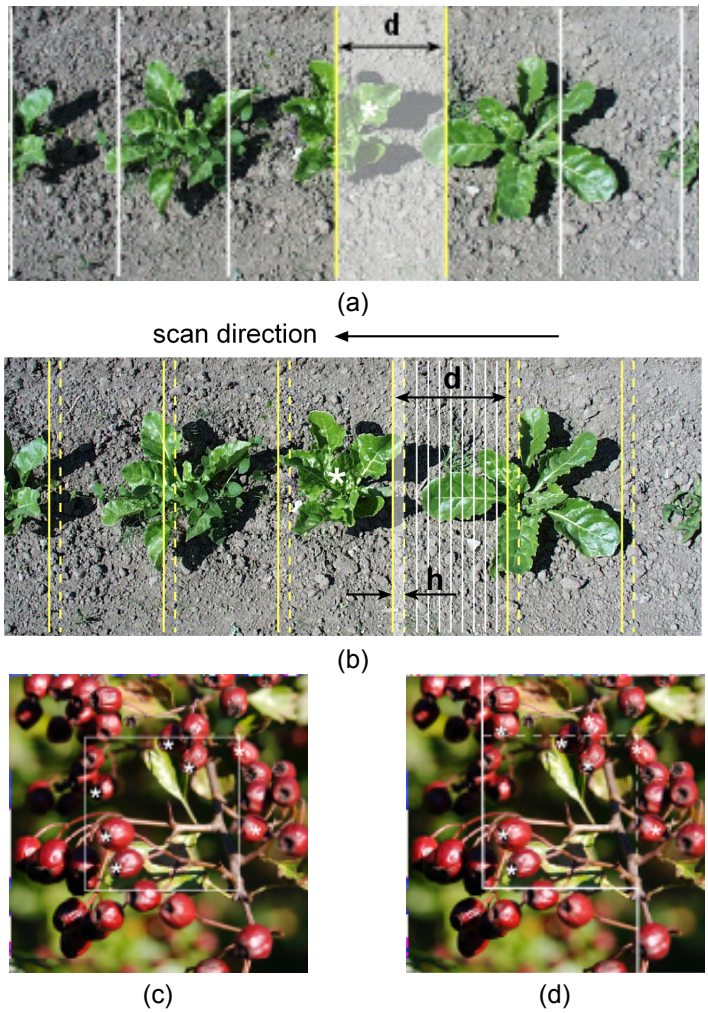


Figure 2.10: Unbiased counting rules used to select objects with equal probability in UR positioned finite windows. (a) 'Disector' or 'first-time' rule (Sterio, 1984). An object is sampled if it overlaps the strip in question but does not cross the right border of the strip (i.e. an object is selected by the first strip which intersects it, when the strips are ordered from right to left). The plant marked (*) is sampled by the highlighted strip. (b) Illustration of 'physical disector' sampling rule (Sterio, 1984). Strips narrower than the horizontal width of any object are used in this example to develop a fractionator with h/d = 1/10 sampling fraction for a 'double systematic subsampling' design. The dashed line is called a counting line while the fulldrawn line is called a lookup line. An object is sampled by a strip of width h if it intersects the counting line but does not intersect the lookup line. The plant marked with an asterisk is sampled by the highlighted strip. (c) Associated point rule (Miles, 1978) samples the 7 fruit indicated with asterisks, which all have their (dimensionless) left tangent point located in the sampling window. (d) Tiling rule (Gundersen, 1978) applied to sample the 8 fruit indicated with asterisks, all of which overlap the window and do not cross the infinite boundary with fulldrawn lines. (Photograph of plants in (a) and (b) by Hans-Werner Griepentrog, University of Copenhagen).

2.8 Remarks

The proper application of sampling principles is necessary to obtain design- or model-unbiased estimators of population attributes and their variability and this is equally true whether variables are measured manually or automated using non-destructive sensors – a machine moving through a field or orchard, equipped with sensors to measure crop yield or structure is performing 'spatial sampling' (Wulfsohn et al., 2004). Equipped with the basic sampling and variance reduction techniques reviewed in this section there is considerable flexibility to design practical sampling protocols for precision farming of soils and specialty crops. Prior knowledge and ancillary information obtained by remote sensing and non-destructive soil and plant sensors can be used within a random sampling framework to design protocols that provide an appropriate balance between statistical precision and cost (time and technology investment).

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3 Yield Monitors for Specialty Crops

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3.1 Introduction

Compared to field crops such as cereals and other commodities, specialty crops such as fruits and vegetables generally require more care and are more sensitive to the growth conditions. Moreover, specialty crops produce relatively high valued products. These characteristics make specialty crops very suitable targets for precision agriculture techniques. According to Brown and Rosenstock (2006), while profitability might be the major consideration in adopting precision agriculture for row crops and similar crops, for specialty crops the lack of suitable technology is the main limitation. Surprisingly, most precision agriculture research and development activities so far have been focused on cereals and little effort has been made to apply precision agriculture methods to specialty crops. This is particularly true for yield monitoring, which is considered to be the logical first step in developing a precision agriculture system.

Yield monitoring is one of the main components of precision agriculture (Pelletier and Upadhyaya, 1999; Rosa et al., 2000). Yield information is needed for successful implementation of precision agriculture. It can quantify the amount of yield variability within a field. Yield monitoring systems are commercially available for grains; however, very few yield monitoring systems are commercially available for specialty crops. Lack of a yield monitoring system is one of the main bottlenecks in applying precision agriculture to specialty crops. The large diversity in the type and harvesting methods of specialty crop as well as the smaller market compared to the row crops have provided little incentive for commercial companies to invest in developing yield monitoring systems for specialty crops.

For most specialty crop producers, knowing the yield early in the season is as important as yield monitoring at the end of the season. Having an accurate yield estimate early in the season is important for growers because it may help them to get a better contract with processing plants. It also helps them to adjust their budget more accurately based on a realistic estimation of income. Yield estimation is either done through a model or through direct counting systems. Models that are used for yield estimation usually include several factors such as yield history, total number of trees, and/or bearing canopy surface area.

Yield monitoring is the process of measuring crop yield for a given location and integrating it with GPS-obtained coordinate information. A yield monitor consists of several sensors. The main sensor is the mass or volumetric flow sensor. Depending on the type, this sensor measures the volume or the actual mass or weight of the fruit. Yield monitors calculate yield by dividing the crop mass/volume that passed

through a mechanical harvesting machine for a given time by the covered area from which the crop was harvested during the sampling period. The yield monitor uses information from ground speed sensors along with the actual operating width of the machine to calculate the area covered by the machine for a given time. Finally, the latitude and longitude information that is obtained from a GPS receiver is indexed to the yield data. This information is usually collected and stored on a memory card at 1 Hz or more. In addition to yield variability, the data obtained from yield monitors contains very useful information for other applications. The yield data can be used to extract machinery management related information such as field efficiency, machine operator performance, total downtime, and actual harvest time. The machine performance information can be very useful to the manager and help in making suitable management decisions to reduce costs and improve efficiency of operation. As shown in Fig. 3.1, mass/volume flow rate sensors, direct batch weighing, and cumulative weighing are the most commonly reported methods used in developing yield monitoring systems for specialty crops. The different methods used to measure mass/volume flow can be categorized as follows:

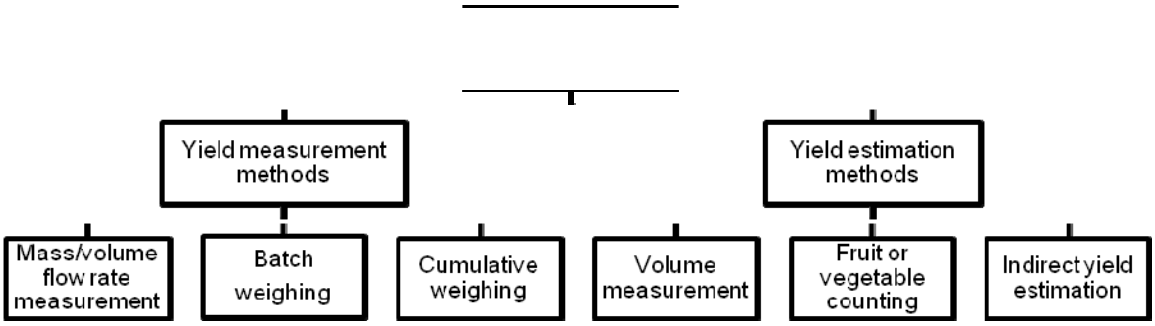

Figure 3.1: Different methods used for yield estimation and yield monitoring for specialty crops.

3.2 Yield measurement methods

3.2.1 Mass flow rate measurement

For mechanically harvested specialty crops, mass or volume measurement of harvested crop is usually done at the end of fruit conveyor belt right before it is delivered into the hauling truck (Figures 3.2a and 3.2b). A typical example of this type is the continuous-weigh tomato yield monitor that was developed by Pelletier and Upadhyaya (1999). This yield monitor measured the weight of the tomatoes on the fruit delivery conveyor belt of a tomato harvester. The mass flow sensor of this yield monitor consisted of two sets of three rollers: a weigh roller at the center and two support rollers, one on each side of the weigh roller. Each set was mounted on the chassis and the conveyor belt sat on the top of these two sets. These sensors were installed along the conveyor belt. Because the inclination angle of the conveyor belt was large and variable, an angle sensor was used to measure this angle and correct the mass flow measurements. Rosa et al. (2000) performed a complete mathematical analysis of this yield monitor. The analysis showed that misalignment of the support rollers can reduce the measurement accuracy. They showed that this problem can be minimized by accounting for the load

cell response under a null load, i.e. when there is no tomato on the conveyor belt. Their analysis also provided important recommendations regarding the arrangement and spacing of the rollers.

Cerri and Magalhães (2005) developed a sugarcane yield monitor consisting of a weigh plate supported by load cells. The yield monitor was installed in the elevator of a sugarcane harvester. Moreover, sensors were used to measure the conveyor inclination and speed. The maximum error of the yield measurements in field was 6.4%. Benjamin et al. (2001) described a similar sugarcane yield monitoring system. They evaluated the system under field conditions for different sugarcane varieties, maturity levels, and flow rates. Results showed that sugarcane maturity level and flow rate did not significantly change the yield monitor readings. However, the effect of sugarcane variety was significant. Molin and Menegatti (2004) also developed a similar system for sugarcane harvesters. Average error in field evaluations was as high as 8%. Lee et al. (2002) used load cells and a moisture sensor to develop a yield monitor for silage. To avoid excessive vibration noise from the harvester, they installed the yield monitor on the silage trailer. Field evaluations showed that this system was accurate within 2% of the total harvested crop. Bora et el. (2006) evaluated a mass-flow citrus yield monitor under controlled laboratory conditions. Their results showed that this type of yield monitor was most accurate if the mass flow rates that are used in the calibration phase are in the same range as those that would be encountered during actual measurements.

A very common type of mass flow sensor is the impact-type mass flow sensor that is also widely used for grain yield monitoring (Figure 3.2c). The harvested crop hits an impact plate that is supported by load cells. The load cell measurements and impact velocity can be used to compute the mass of the crop. For impact-type yield monitors to be accurate, the coefficient of restitution of the fruit or vegetable should be known accurately. The coefficient of restitution of an object is a value representing the ratio of its velocity before and after an impact. An object with a coefficient of restitution of 1 collides elastically, i.e. it bounces with the same velocity after the impact. An object with a coefficient of restitution of 0 will stick to the object that it collides with. If the coefficient of restitution of a crop significantly depends on its maturity, moisture content, and the like, impact-type yield monitors will not result in accurate measurements (Pelletier and Upadhyaya, 1999). Analysis of this type of yield monitors requires a knowledge of basic impact mechanics and can be found in Upadhyaya et al. (2006).

Qarallah et al. (2008) developed an impact-type yield monitor for measuring the mass of individual onion bulbs. A cushioned impact plate, supported by two load cells, was placed at the end of the conveyor belt. The system was able to measure the mass of individual onion bulbs with an error smaller than 2%. The accuracy of the measurements was independent of the orientation of the onion bulbs on the conveyor belt or their orientation as they hit the impact plate. Upadhyaya et al. (2006) developed two impact-type continuous tomato weighing systems. In one design, four load cells were used to measure the impact force, while in the second design a single load cell was employed. In both systems, the impact plate was placed at the end of the conveyor boom. In order to find the speed of the tomatoes, a magnetic sensor was used to measure the speed of the conveyor. Both of the yield monitors provided very accurate measurements under field conditions. However, calibration drift was a problem and they recommended a need to isolate the impact unit from the vibration frequencies associated with the harvester (Personal communications with Dr. S. K. Upadhyaya, Professor, Bio. and Agr. Eng. Department, University of California at Davis).

3.2.2 Batch weighing

In this design, the continuous flow of crop is converted into batches and each batch is weighted before it is delivered to the hauling truck. Figure 3.2e shows a schematic view of this concept. Abidine et al. (2003) and Cerri et al. (2004) describe the development and improvement of a weigh-bucket type yield monitor for tomato. This yield monitor included a weigh bucket that was mounted on the end of a tomato harvester boom. Four load cells continuously weighed the tomatoes in the bucket. Field evaluations showed that the output of the yield monitor measurements was highly correlated with the true weight of the harvested tomato ($r^2 = 0.99$). A similar type of yield monitor was developed by Heidman et al. (2003) for pistachios. The yield monitor was installed and tested on a commercial pistachio harvester in the field. The coefficient of determination between the true yield and the measurements was 0.97.

3.2.3 Cumulative weighing

Cumulative weighing systems have been used mainly where the harvested crop is collected in a container on the harvesting machines or a hauling truck (Figure 3. 2g). These types of systems measure the total weight of the harvested crop over time. They are usually very accurate in measuring the cumulative weight. However, in order to find the instantaneous yield, as in yield mapping, the rate of increase of the cumulative weight has to be computed. Vellidis et al. (2001) developed and tested a cumulative weighing system for yield monitoring of peanuts. Details of this type of yield monitor development are presented in Thomas et al. (1999). The system used load cells to measure the weight of the collection basket in the peanut harvester. Major potential sources of error were identified and studied. The error due to sloping terrain was negligible. The noise due to vibrations of the harvester and uneven field surface were measured and dealt with appropriate filtering. The time lag of the harvester was also estimated. The system was evaluated during three harvesting seasons. The results indicated that the measurements were within 1% of the true weight.

Rains et al. (2002) developed a similar yield monitoring system for pecans. One of the challenges was to estimate the weight of the foreign material that is picked up by the harvester. The authors conducted field experiments and developed a simple linear equation to estimate the net pecan yield from the gross weight of the pecan and the foreign material. The yield measurements were closely correlated with the true yield for the individual pecan trees ($r^2 = 0.84$). Behme et al. (1997) used a drawbar load cell and two weigh axle load cells to estimate the bale weight in a round baler. The bale weight was estimated by summing the output of three load cells. Field experiments were performed to evaluate the accuracy of the system. The overall error was between 2.5% and 5.2%. Wild and Auernhammer (1999) used a series of strain gauges to build a yield monitoring system for a round baler. Similar to the work of Behme et al., strain gauges were installed on the drawbar as well as on the baler axle. The measurement errors in field experiments were less than 1%.

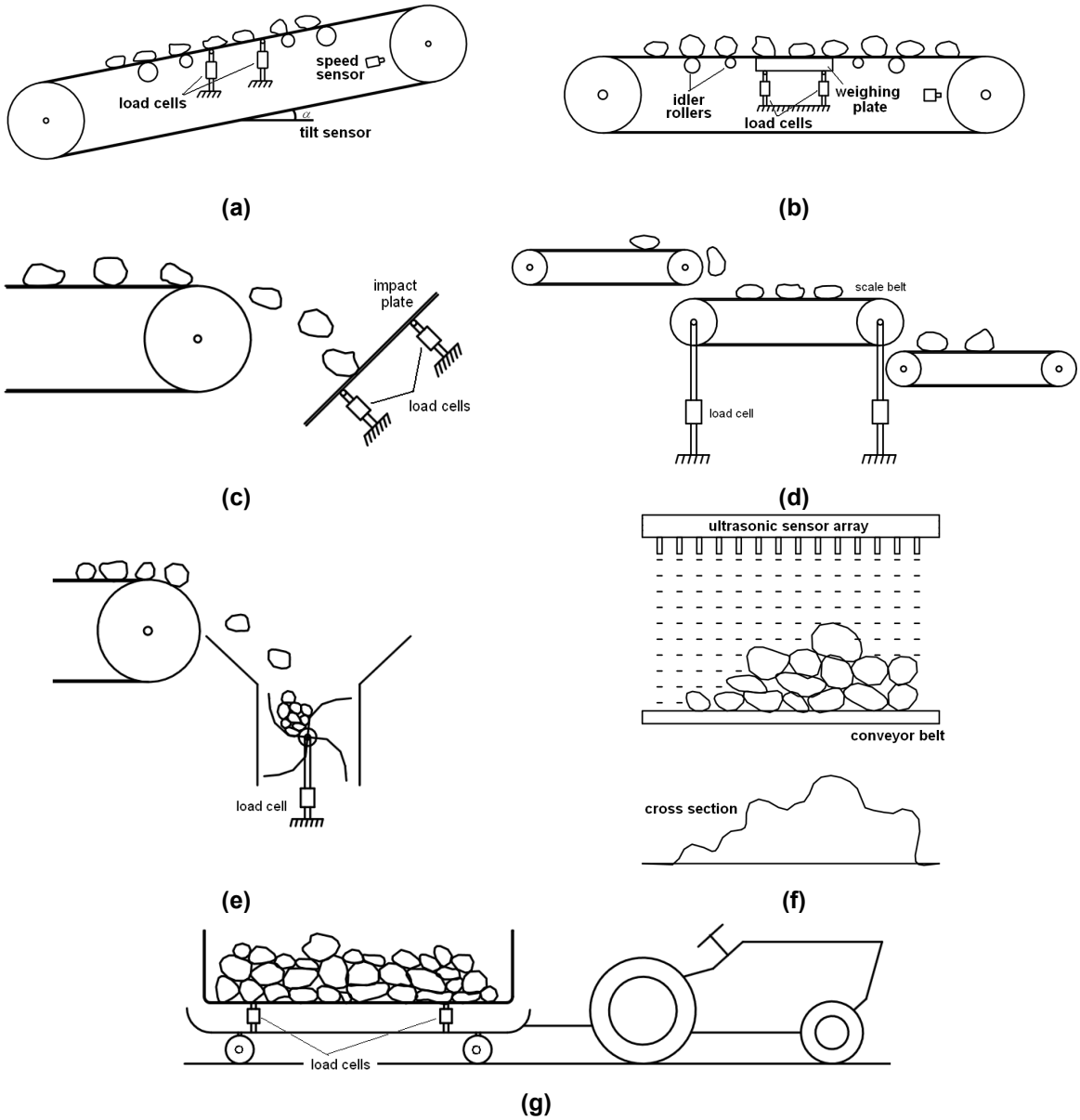

Figure 3.2: Schematics of common yield monitoring systems for specialty crops

3.2.4 Volume or volumetric flow rate measurement

These systems aim to first estimate the volume or the volumetric flow rate of the crop and then convert it to a mass value (Figure 3.2f). Computer vision or optical techniques such as the laser scanners are widely used for this purpose. Persson et al. (2004) tested an optical sensor for measurement of the size of tubers. Laboratory tests with perfectly spherical objects showed that the optical sensor was very accurate in measuring the number and size of the objects. Also, the measurements were very

robust to the changes in the tilting of the camera or the position of the tuber with respect to the center of the camera's field of view. Field experiments on a commercial potato harvester showed that the correlation between the number of pixels in the tuber image and the tuber weight was r^2=0.91. The authors believed that the errors were due to the differences in the tubers' orientation with respect to the camera and the moisture content. Comparison of the optical sensor with a load cell in the field experiment showed that the mean of the optical sensor deviations from the load cell measurements was 3.2%. Gogineni et al. (2002) developed a computer vision-based yield monitor for sweet potato. In order to recognize sweet potatoes from the soil clods, the images captured by a digital color camera were transformed from RGB space into a new space in which pixels were characterized by their luminance and chrominance. Sweet potatoes were detected in the new space by color thresholding, edge detection, and segmentation. Then, for each sweet potato detected in the image, area, polar moment of inertia, rectangular width and height, and major and minor axes were computed. Different combinations of these features were used to develop multiple linear regression and neural network models for estimation of sweet potato weight. Best results were achieved when all the features were used by the algorithm. Both methods were able to provide very accurate estimations, but the multiple linear regression method was more accurate ($r^2 \geq 0.95$). The system was installed on commercial potato harvesters and tested under real field working conditions. The coefficient of determination between the number of sweet potatoes detected by the image analysis algorithm and manual count was $r^2 \geq 0.91$ for the neural network method and $r^2 \geq 0.80$ for the discriminant analysis method. The authors attributed the reduced accuracy to muddy field conditions and poor lighting in the boundaries of the field of view of camera. Bora et al. (2006) developed a similar system for citrus fruit yield estimation. Evaluation of the system in the laboratory showed that it was very accurate in identifying the fruits that appeared as full in the image. However, when the fruit image was not complete, the recognition error rates were very high. The overall fruit detection accuracy was 85%.

Konstantinovic et al. (2008) used an ultra-wideband (UWB) ground penetrating radar system to detect sugar beets in soil. The system was successful in detecting the sugar beets (success rates higher than 90%). Moreover, the authors were able to relate the reflected energy to the mass of individual sugar beets with a correlation of 83%. Laboratory evaluation of the system showed that the detectability of an object buried in the soil depended on the size of the object, the depth of the object in the soil, the soil moisture content, and roughness of the soil surface. Smaller and deeper objects were more difficult to detect, and high moisture contents and rougher soil surfaces were less favorable. However, the authors were unable to develop a computer algorithm for automatic detection of the sugar beets from the reflected energy curves.

Rains et al. (2005) used two optical sensors to build a peanut yield monitor. They installed the sensors in the delivery chute after the air fan. Specific attention had to be paid to ensure that the sensors were not covered by dust. The yield monitoring error was 3-9% under real harvesting conditions. The authors suggest that in order to keep the errors at minimum, the yield monitor be recalibrated every time the field conditions or harvester adjustments change. Thomasson et al. (2006) also developed an optical yield monitor for peanut. Field evaluation on commercial peanut harvesters showed that this yield monitor was capable of estimating peanut yield with very high accuracy. The coefficient of determination between the two optical sensor outputs and true peanut weight was 89-96%. The authors mentioned peanut moisture content and nonlinear behavior of the sensor output for high mass flow rates as two major challenges that need to be addressed to further improve the accuracy. Price et

al. (2007) developed an optical yield monitor for sugarcane harvesters. The system consisted of three optical sensors on the floor of the conveyor. The sensors were very rugged and required no maintenance after working for very long hours. The estimated yield was strongly correlated with the true yield ($r^2 = 0.93$). In a similar study, Cundiff and Sharobeem (2003) developed a volumetric yield monitoring system for round balers. Displacement sensors were used to measure the windrow cross section. This measurement and the velocity were used to compute the volumetric flow rate, which was then multiplied by a mass factor to give the mass flow rate. Field experiments showed that the yield estimations were within 4% of the true value. Chinchuluun et al. (2006) developed a computer vision system for counting the number of citrus fruits on the harvester conveyor belt. A Bayesian classifier was used to identify citrus fruit pixels in the identified image. The system was able to detect the individual citrus fruits with high accuracy in the laboratory ($r^2 = 0.96$) and during real field harvesting on a canopy shake and catch harvester ($r^2 = 0.89$).

3.3 Yield monitoring for hand-harvested crops

With hand-harvested crops, yield monitoring systems use a technique to record the weight of the fruit or vegetable in a bucket, basket or container and geo-reference it right before it is delivered to the hauling truck. In some cases, if the weight of the container is constant, the yield monitoring system only records the location of the containers. An example is the system developed by Whitney et al. (2001) for yield mapping of hand-harvested citrus. Their system was based on measuring the weight and location of each tub that was picked up by a hauling truck. Field evaluation of this system showed that a hydraulic cylinder option provided more accurate measurements than a shear-beam load cell system. However, this higher accuracy may have been due to different measurement methods that were employed. The output of the load cells were recorded every 0.1 s and the yield was computed by discarding the smallest and the largest measurements obtained during every second and calculating the average of the remaining eight measurements, whereas for the hydraulic cylinder, the pressure was measured manually using a voltmeter after the display had stabilized. Tumbo et al. (2002) used limit switches to detect when a tub was picked up by the hauling truck. Field evaluation showed that this system was accurate 89% of the time. These systems were interfaced to a GPS unit to map the location of each tub in the field.

3. 4 Yield estimation methods

These systems use computer vision and other technologies to count the number of fruits or to measure the volume or other characteristics of the harvested crop. They include non-contact, non-intrusive measurements which could be a major advantage for certain crops. On the other hand, all these systems require that some characteristic of the crop such as the density or the mass of individual fruit be constant.

3.4.1 Volume estimation

These systems aim to estimate the volume or the volumetric flow rate of the crop. Zaman et al. (2008), for example, used a color camera to take top-view images of wild blueberry crop at harvest time. They developed a computer program to count the number of blue pixels in each image. The true blueberry yield was determined by hand-harvesting and a linear regression analysis was performed to relate the

percentage of blue pixels in each image to the blueberry yield. The analysis showed that the two variables were significantly correlated with a very high coefficient of determination ($r^2 = 0.98$). The regression model developed based on the observations in one field was used to predict the blueberry yield in a different field. The model predictions were very close to the true yield ($r^2 = 0.99$). The proposed approach was also robust to changes in illumination.

3.4.2 Yield estimation by counting individual fruits or vegetables

The goal of these yield estimation systems is to count the number of fruits, tubers, etc. on the tree or in the harvester. Count of the number of fruits and the estimation of average mass of an individual fruit is used to estimate yield. Annamalai et al. (2004), for example, developed a machine vision system for counting the number of citrus fruits on a tree. They used a color camera installed on a truck to take images of the tree canopy and estimated the number of fruits in each image by analyzing the image. The developed algorithm was relatively successful in detecting the individual fruits. The errors were attributed to uneven illumination, fruit occlusion, and fruit clusters. The yield prediction model that was developed using this technique was not very successful ($r^2 = 0.53$). The authors suggest the use of improved imaging techniques such as automatic brightness control and multiple cameras for better results. Ehsani et al. (2009) used photo interruption sensors to count individual citrus fruits. The mass flow of the fruits was singulated into five channels and the sensors counted individual fruits at the channel exits. The system was able to count individual fruits 99.8% of the time under laboratory conditions. An alternative theoretical method based on the assumption that fruit arrivals at the sensor is a Poisson process failed because laboratory experiments showed that this assumption was not valid.

3.4.3 Indirect yield estimation

These methods estimate the yield by measuring some related parameter(s) such as tree canopy size. Zaman et al. (2006) found that measurements of citrus tree canopy size can be used to estimate the yield. They used an ultrasonic sensor to measure the volume of the tree canopy. They also mapped the yield by recording the location and weight of fruit tubs as they were picked by a goat truck. Analysis showed a strong correlation between the tree canopy size and yield ($r^2 = 0.80$). The regression model was used to estimate the yield based on canopy size for a set of new trees. Although the estimated and true values of fruit yield were significantly correlated, the data spread was large ($r^2 = 0.42$).

Ye et al. (2008) used aerial hyperspectral imagery to estimate the yield of individual citrus trees. They used the two-band vegetation index (TBVI) and multiple linear regression analysis to relate the spectral characteristics of the pixels of a tree canopy in the image to the yield of the tree. Analysis showed that the yield was highly correlated with the hyperspectral image from the period of fastest vegetation growth. The authors believe that due to the alternate bearing of citrus trees, the size of tree canopy alone cannot be used to estimate the yield. Instead, canopy size should be used along with TBVI to predict the yield. These two variables together explained 76% of the yield variability.

Hall (2009) reported interesting results regarding the relationship between the grapevine canopy size and vegetation density and grape yield. He found statistically significant relationships between the

grapevine canopy density and grape yield in the same year. Also, the canopy density at flowering stage in one year was significantly correlated with the yield in the next year. This study suggested that canopy area and density information from the previous years can be useful information in predicting next year grape yield.

3.5 Processing yield monitor signal

There are three major concerns with the data collected from mass/volume flow sensors used for specialty crops: i) background noise contamination of signal, ii) harvester lag and iii) mixing of the harvested material. Yield monitors that use load cells or other means to measure forces, can be very sensitive to the vibrations in the system. It is necessary that the output of these yield monitors be filtered to remove the vibration noise before sampling in order to avoid aliasing. The frequencies to be filtered should be determined by investigating the range of frequencies in the sensor output that contain useful information and the frequency spectra of machine vibrations.

Magalhães and Cerri (2007) found that vibration frequencies on a sugarcane harvester ranged from 30 to 200 Hz and useful yield information was limited to 4 Hz. They used an analog Butterworth low-pass filter with a 9 Hz cut-off frequency to filter the load cell output. Abidine et al. (2003) found significant high frequency vibrations (with peaks at 18, 36, and 45 Hz) in the load cell signal in a weigh-bucket type tomato yield monitor. Durrence et al. (1997) observed a major vibration noise at a frequency of 4.7 Hz in a peanut yield monitor output. They found that this signal was caused by the combine's straw walker. Pelletier and Upadhyaya (1999) analyzed the vibration frequencies in the output of a tomato yield monitor. They used a low-pass filter with a corner frequency of 30 Hz and a stop-band of 100 Hz to filter the load cell output. Upadhyaya et al. (2006) used a notch filter to remove the DC (gravitational) component of a load-cell type yield monitor. A simpler alternative to standard filters is the moving average method. Cundiff and Sharobeem (2003) used a 10-point moving average method for smoothing the yield measurements of a volumetric forage yield monitor. Lee et al. (2002) used a 15-point moving average for a load-cell type silage yield monitor. Wild and Auernhammer (1999) used spline smoothing and low-pass filtering to remove vibration noise in a baler yield monitor.

Harvester lag refers to the time delay between the moment the fruit or vegetable is picked up by the harvester and the moment it is sensed by the yield sensor. The range and variation of this lag should be measured and analyzed for each specific harvester and crop. In yield mapping, the harvester lag and forward speed are used to correct the yield measurements. Pelletier and Upadhyaya (1999) measured the time delays for a tomato harvester. They found 2-s delays due to fruit build-up and a 3-s delay at the rear cross conveyor. They modeled each of these delays by a first-order transfer function. Heidman et al. (2003) found that the harvester lag in a pistachio harvester largely depended on the speed of the conveyor belt and could be reduced from approximately 1 min to less than 10 s by increasing the conveyor belt speed.

However, studies show that transport of material in the harvesters cannot be characterized by a simple delay time. Usually a significant mixing of the materials that enter the harvester at different times occurs. Vellidis et al. (2001) studied this phenomenon in a peanut combine. They input the combine with a 1-s pulse of material and observed that it took 45 s for the material to entirely reach the basket. They suggested that the harvester lag can be defined as the time required for 50% of the material to reach the basket.

Durrence et al. (1999) characterized this mixing behavior by finding the corresponding impulse response and used deconvolution to account for the effect of mixing. Although their approach seemed very natural and clever, it was not successful and a simple time lag of 13 seconds provided better results. Boydell et al. (1999), however, found that deconvolution method was more accurate. Their experiment and analysis with a two-row peanut combine showed that the deconvolution method provided lower errors and better spatial resolution compared to a time lag.

Rains et al. (2002) also encountered the mixing problem when they used a pecan harvester and yield monitor to measure the yield of individual pecan trees. As expected, usually pecans from two or more trees were picked by the harvester simultaneously. In other words, there was an overlap between adjacent trees. Rains et al. used the fact that there was a peak in yield monitor signal when the harvester was near a tree trunk. Analysis showed that a window of 4-6 m around the tree trunk provided the highest correlation with the yield of the individual tree ($r^2 = 0.84$).

3.6 Yield mapping

Figure 3.3 shows a yield map for a section of a citrus orchard which is overlaid on top of the aerial image. The yield map demonstrates the yield variation pattern with a high production area roughly in the center of the orchard. The amount of variability between high yield and low yield is about 50% which is a very significant yield difference that was not recognized by the grower who previously harvested the block as a whole. Yield variability could be caused by several factors. The major causes of yield variability in a citrus orchard are due to variability in tree size, soil type, elevation, extent of pest infestation, and/or disease infection. Zaman et al. (2006) reported that the yield in a citrus grove varied between 21 and 45 Mg/ha, whereas Tumbo et al. (2002) found a range of 9 to 54 Mg/ha.

Persson et al. (2004) reported that the variability in potato yield measured by a yield monitor was from 40 to 100 Mg/ha. Field studies by Price et al. (2007) showed that average sugarcane yield was approximately 76 Mg/ha, but the local yield varied between 36 and 214 Mg/ha. Molin and Menegatti (2004) used a yield monitor to map two sugarcane fields. The range of yield variation was 15-200 Mg/ha in one field and 18-150Mg/ha in the other. In another study, Magalhães and Cerri (2007) found a range of 6-150 Mg/ha for sugarcane yield variability in a specific field. Thomasson et al. (2006) generated peanut yield maps using a peanut yield monitoring system. For the specific field in their study, the average yield was 3 Mg/ha, but the local yield varied from below 1 Mg/ha to as high as 6 Mg/ha. In field measurements reported by Heidman et al. (2003), the yield of individual pistachio trees varied between 6 and 78 kg. The mean yield of 6000 trees was 38.8 kg with a standard deviation of 12.1 kg.

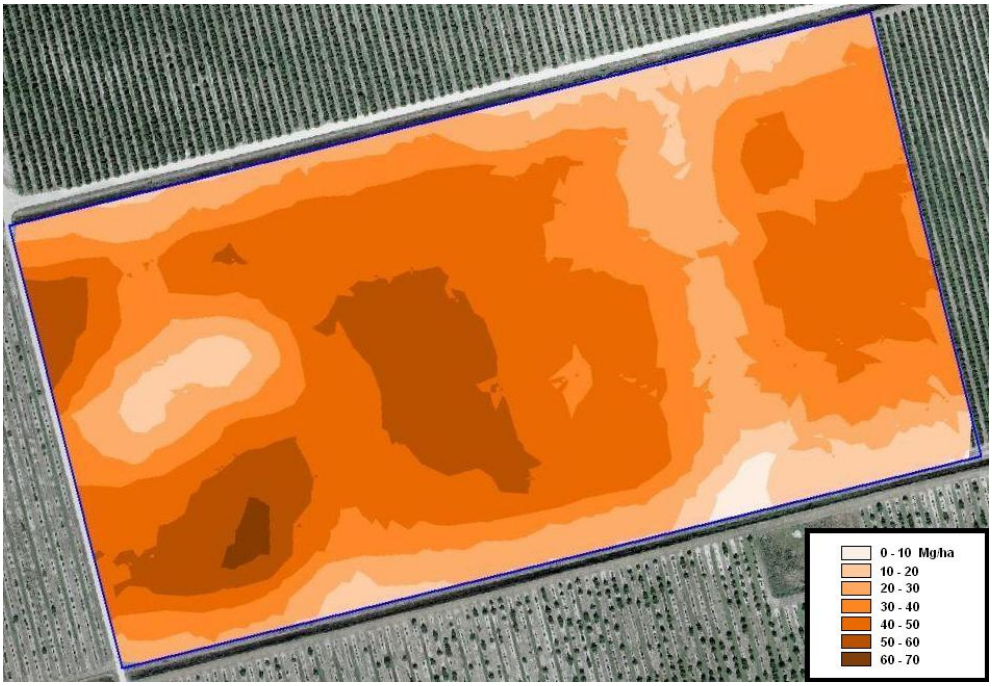

Figure 3. 3: Contour yield map of a citrus orchard, Fort Basinger, FL.

3.7 Remarks

Yield monitoring for specialty crops has its own challenges. Some specialty crops are highly sensitive to mechanical damage. This can be a very important consideration in designing certain types of yield monitors for these crops. In addition to spatial variability, some specialty crops such as citrus show very high temporal yield variability due to inherent alternate bearing characteristics of the crop. Therefore, growers are very interested in methods that can predict the yield well before the harvesting season. This manuscript reviewed the important previous work on yield monitoring for specialty crops.

Mass flow rate sensors measure the mass of the crop as it moves on a conveyor or the impact force as the crop collides with a plate. They have provided relatively accurate yield measurements for a wide range of crops. Batch and cumulative weighing systems have been developed for a variety of crops and usually provide accurate measurements. Many yield monitoring systems use cameras, optical sensors, or similar sensors to measure the volume or volumetric flow rate of the crop. The output of these sensors is in such forms as images or reflectance spectra which require more sophisticated processing compared to a load cell signal. These types of yield monitoring systems involve non-contact sensing techniques and have provided relatively accurate yield measurements for various crops. Yield estimation systems try to estimate the crop volume or to count the number of fruits or vegetables and relate it to crop yield. Early estimation of crop yield by measuring the volume or spectral characteristics of the tree canopy have also been relatively successful for citrus and grapes. These methods provide the opportunity to predict the yield before the harvesting season.

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4 Precision Irrigation

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4.1 Introduction

Specialty crop production and processing systems are heavily dependent on the availability and quality of water resources in the United States. More than 90% of the major specialty crops in the United States are irrigated, with most receiving annual water application amounts greater than .25 ha-m (2 A-ft), with higher amounts in arid areas like AZ and CA and in crops like cranberries in MA (Table 4.1). Large quantities of water are used in fruit processing and management of processing waste water is also a major water quality concern. Not only are the majority of specialty crops irrigated, but the water resources used for irrigation are subject to significant competing uses and threatened by a range of water quality concerns (Gleick, 2003; Kassam et al., 2007; Sadler et al., 2007). There are perhaps no better examples of the stress on water resources particularly relevant to irrigated agriculture than the Colorado River and the Ogallala Aquifer (NRC, 2008) and recent outbreaks of contaminated vegetables from pathogens in the irrigation water (Associated Press, 2008). The science of irrigation is well understood and irrigation technologies today are mature and very robust (Hoffman et al., 2007 and Lascano and Sojka, 2007). However, concerns over water availability and water quality increasingly require more efficient use of water resources in irrigated agriculture. Evans and Sadler (2008) suggest that “the competition for existing freshwater supplies will require a paradigmatic shift from maximizing productivity per unit of land area to maximizing productivity per unit of water consumed”.

Table 4.1: Irrigated acres and water application amounts for selected specialty crops in the United States (USDA, 2004).

Crop	*Irrigated*	*Non-irrigated*	*Irrigated*	*Water Use acre ft*	
	Acres		*%*	*National*	*Average*
				State	*Maximum*
Potatoes	1,032,604	26,275	97.5	1.8	3.3 (AZ)
Vegetables	2,081,358	137,765	93.8	2.1	4.4 (WY)
Tomatoes	427,812	2,167	99.5	2.6	2.8 (CA)
Lettuce and romaine	276,705	340	99.9	2.7	3.6 (AZ)
Orchards,vineyards, nuts	4,104,946	119,778	97.2	2.2	5.2 (AZ)
Berries	229,542	21,705	91.4	2.1	6.7 (MA)

The seriousness of the concern over water availability is evident in the recent passage (July 30, 2008) by the U.S. House of Representatives The Water Use Efficiency and Conservation Research Act (H.R. 3957) that would establish a water-use efficiency and conservation research and development program within the EPA's Office of Research and Development. Precision irrigation is considered an important technology for improving water use efficiencies in both continuous move and fixed irrigation systems (Evans and Sadler, 2008).

4.2 Overview of precision irrigation

We begin our discussion with a summary of the major points reported in two major reviews of precision irrigation recently published by Camp et al. (2006) and Sadler et al. (2007). Precision irrigation is not a new term in irrigation, as being precise about the uniform application of water has long been a goal of irrigation science. The new dimension of precision irrigation is accounting for the spatial dimension of water management, i.e., applying water based on the site-specific needs of a given location in the field. While these authors describe precision irrigation as conceptually simple, they report that it has been primarily a research issue emerging in the early 1990's, with the majority of development done in continuous move irrigation systems because they are particularly amenable to site-specific approaches because of their current level of automation. There are limited examples of commercialization, with the implementation efforts in Georgia noteworthy (Milton et al., 2006). Precision irrigation in fixed irrigation systems, used particularly on small farms or in high value crop production systems (e.g., tree fruit) has been limited. The research focus has been primarily on the control aspects of precision irrigation, with more efforts including real-time monitoring of soil and crop conditions to trigger site-specific irrigation. They recognize the most serious limitation to the execution of precision irrigation is lack of site-specific production functions that optimize water use at a given site at a given time resulting from an insufficient knowledge base to make management decisions. Commonly, whole field recommendations are applied on a more spatially precise scale. They emphasize that precision irrigation systems must incorporate agrochemical (fertilizer and pesticide) applications to be cost effective and therefore profitable. Position and alignment technologies are required to use spatially indexed data to set application rates for various sites within a field. The cost of global positioning systems (GPS) with required accuracy has been the greatest challenge in positioning, although very recent cost reductions and miniaturization of GPS technology may alleviate this problem. Errors in water and agrochemical application rates are associated with transition zones where irrigation rates change which are related in part to nozzle configurations, for example, how many nozzles are grouped into zones along an irrigation span. In the future, these reviews suggest that growing demand for irrigation water, competition for water resources, depletion of existing water resources, and water quality concerns will likely be the drivers for the development and implementation of precision irrigation.

The underlying notion is that improved irrigation water use efficiency in agriculture can be achieved by better targeting of water both spatially and temporally to more precisely meet the site-specific water requirements of plants while concomitantly improving environmental quality of irrigated cropland. Camp et al. (2006) call this approach to irrigation precision irrigation, which they defined in terms of "site-specific water management, specifically the application of water to a given site in a volume and at a time needed for optimum crop production, profitability, or other management objectives at that specific site". We accept this as our operational definition for precision irrigation in the remainder of our discussion. While the majority of work on precision irrigation deals with continuous move irrigation systems, primarily center pivot and linear move systems, recent advances have also been made for

fixed irrigation systems, for example, for tree fruit (Coates and Delwiche, 2008). Precision irrigation in continuous move irrigation systems has evolved since the first system was reported in 1992 by Fraisse et al. (1992) and Duke et al. (1992). Our intent is not to repeat the recent literature reviews but rather to provide an overview of precision irrigation as it relates to irrigation water management in specialty crops. To that end, our discussion will focus on three critical aspects of precision irrigation: 1) control of irrigation amount and timing for a given site, 2) determination of the irrigation requirement for a given area for a given crop, and 3) assessing the value proposition.

4.3 Spatial variability

The underlying rationale for precision irrigation is the presence of spatial variability within an irrigated field that affects water availability (sufficiency or excess) to a crop, limits crop yield or quality thereby affecting crop water demand, or regulates water application due to erosion, runoff, leaching or other environmentally sensitive problems. Common sources of within field variability derive from variation in soil properties and topography, either naturally occurring or induced by human management (e.g., compaction, erosion, organic matter depletion) that in turn regulate soil water holding capacity, soil and terrain hydrologic properties, and nutrient supply. Nielsen and Biggar (1973) were one of the first to quantify the within field variability of field-measured soil water properties in an irrigated field. Clay content, C content, and tillage method were reported by Pires da Silva et al. (2001) to influence soil water storage patterns. Topographic factors, specifically elevation, slope and curvature, were found by Tomer and Anderson (1995) to explain 51–77% of spatial variability in soil water content in a sandy hill slope. New technologies for mapping soil properties, specifically soil electrical conductivity (Corwin and Lesch, 2005; Hedley et al., 2004), have revealed considerable within field variability that could guide site-specific irrigation (Brevik et al., 2006; Chiericati et al., 2007; Farahani, and Buchleiter, 2004; Hedley and Yule, 2009). Camp et al. (2006) suggest precision water management may be required in fields containing ground water recharge zones in order to meet regulatory statutes or to limit water application to areas with poor infiltration rates in order to achieve trafficability for farm equipment to optimize field operations. There can be considerable non-crop acreage within a field including drainage ditches, waterways and structures for which irrigation is not required. For 33 irrigated fields, Milton et al. (2006) reported the noncrop acreage covered by pivot irrigation system ranged from 0.08 to 15.8 ha in fields 4.45 to 133.3 ha, respectively, averaging 6.9 ha. Site-specific irrigation may only change the timing and not the amount of irrigation applied. King et al. (2004) reported gross receipts were approximately \$159 ha^{-1} greater under site-specific water management compared to conventional uniform irrigation management for potato primarily due to improvements in tuber quality rather than increased yields.

The key to success in precision irrigation is applying the correct amount of water at the right time to meet the water requirements of a crop and that requires accurate knowledge of the within field production functions for all locations within a field. As we discuss later, lack of knowledge of site-specific production functions is a major limitation for precision irrigation (Camp et al., 2006; Sadler et al., 2007).

4.4 Irrigation control

The design of any precision irrigation system for continuous move systems (center pivot or linear move) must include the ability to control the water application volume per unit area at any time or place

in the field. Note that the unit area may not be the same either within the field or from one irrigation event to another depending on how the irrigation requirement is determined. Unit area may vary when agrochemicals are site-specifically applied in a given irrigation event since these application maps may not correspond to the water application map. Volume control per unit area has been achieved by varying the application rate of the sprinkler(s) and/or controlling the ground speed of the continuous move system. While the ideal technology is a variable rate sprinkler with a range of water application rates, such as the variable orifice method conceived by King and Kincaid (1996), the most common approaches have been the pulsing of nozzles on and off over a fixed time cycle or the use of multiple-nozzle system each with a different application rate that provide a range of water application rates depending on which nozzles are operational at a given time (Camp et al., 1998). Refer to Camp et al. (2006) for a detailed discussion of various control systems for continuous move irrigation systems.

A recent example of a precision irrigation control system for continuous move irrigation systems is the remote, real-time irrigation monitoring and control system (RIMCS) developed by Chavez et al. (2010a),with recent modifications by Pierce and Elliott (2008). The system consists of individual nozzles connected to a 24 VAC solenoid/control valve wired to a nozzle node controller developed by Pierce and Elliott (2008). The nozzle controller accommodates other electronic devices so that sensors, such as flow, pressure, and GPS position can be monitored. A single wire carries power and communications from the nozzle controllers to a master controller located at the linear move cart (Figure 4.1). The master controller is a single board computer connected to a remote server via wireless radios. Water application rate is varied by pulsing nozzles on and off for a set number of seconds over a 1 minute cycle. The on/off times are determined by a water application map that is sent to the master controller via a wireless internet connection as depicted in Figure 4.2. Field tests of the RIMCS system on two different linear move irrigation systems installed in Washington State and in North Dakota showed accurate water application accuracies were achieved over a range water application rates (Chavez et al., 2010b).

For fixed irrigation systems (orchards, groves, vineyards, berry fields, and nurseries), nozzles or emitters are fixed so spatially variable control requires a network capable of controlling a large number of sensors and valves (Miranda et al., 2005). Two strategies have been used to spatially vary irrigation rates in fixed irrigation systems. One is individual nozzle or emitter control, the other is zone management.

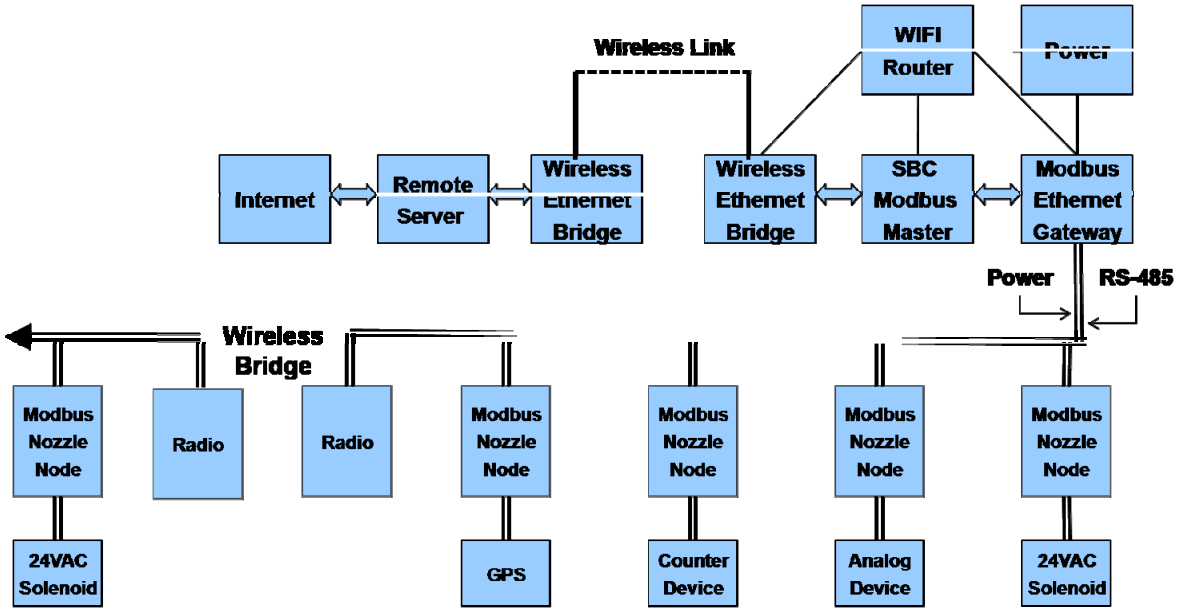

Figure 4.1: Conceptual diagram of a MODBUS RTU, multi-drop bus irrigation control system (Pierce and Elliott, 2008). The upper portion of the diagram illustrates the control system and wireless interface with a remote server. The lower portion illustrates that the bus accommodates the solenoids, analog and counter devices and a GPS device and can be extended via a wireless bridge. The SBC is the main controller and the nozzle node is the nozzle controller.

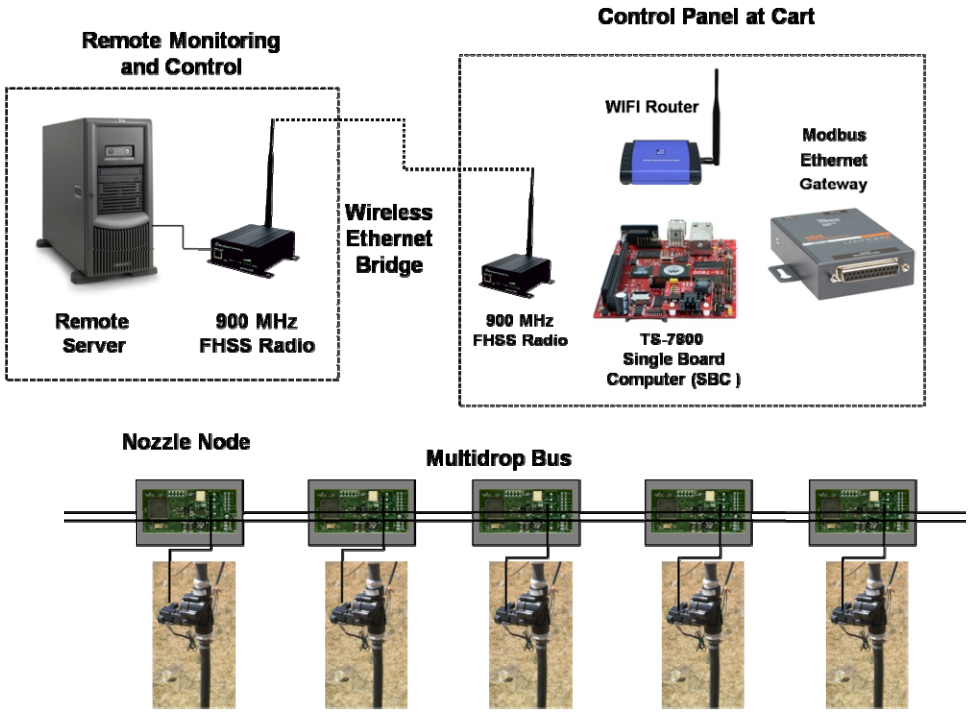

Figure 4.2: Illustration of the multi-drop/RTU bus for the linear move irrigation at Prosser, WA (Pierce and Elliott, 2008).

Zone management in fixed irrigation systems has been approached in a variety of ways. Torre-Neto et al. (2000) installed multiple lateral lines in citrus grove rows in order to vary water application rates according to tree size. Nemali and van Iersel (2006) developed an irrigation controller that irrigates substrates in potted plants to a set-point volumetric water content and maintains that water content close to that set-point for several weeks. The controller uses calibrated, dielectric moisture sensors, interfaced with a datalogger and solenoid valves, to measure the volumetric water content of the substrate every 20 min. Irrigation is triggered when the water content goes below the set point to maintain a constant water content in the container. Owen (personal communication, 2008) employed a similar system in Oregon to control irrigation in nurseries by potted plant type. Miranda et al. (2005) implemented a low cost, solar-powered feedback controller that uses sensed soil water potential (SWP) measurements to control the amount of water applied to specific irrigation management areas within a field delineated based on soil characteristics, crop water requirements, and/or economic factors. For each irrigation management unit, an irrigation controller is installed that monitors three SWP sensors, soil temperature, system pressure, and controls a solenoid valve for irrigation. The controller autonomously controls the soil water potential (SWP) between field capacity (FC) and management allowed deficit (MAD) by triggering an irrigation event when two sensors indicate that SWP falls below the MAD. Irrigation continues until two sensors indicate that the SWP exceeds the MAD. A large scale version of zone management is the valve control and meter reading system developed by Damas et al. (2001) for centralized remote control of large irrigated areas with a large number of individual control points. Commercial irrigation companies also offer systems that monitor and control multiple continuous move via the Internet. Pierce et al. (unpublished) developed a remote, real-time wireless control system to monitor and control fixed irrigation system in a research cherry orchard in Washington State. The system included a relay board and a data logger/900 MHz frequency hopping, spread spectrum radio configured in a point-to-multipoint network with a base located at a remote site connected directly to the internet. The orchard had two drip lines installed in each row and three zones of microsprinklers per row, each controlled by a solenoid (Figure 4.3). A flow meter and pressure sensor were installed in the water supply line. A microprosser on the datalogger/radio contained an irrigation control program that could be updated via the radio network, with communication set by the user to a set time interval for logging pressure and flow. Flow rates can be calculated from flow rate and nozzle output ratings over time.

Individual nozzle or emitter control systems designed to vary water and fertilizer rates to individual trees have been reported by Coates et al. (2006a, b). Their system used individually addressable microsprinkler nodes and a drip line controller that stored the irrigation schedule and issued commands to each node. Each microsprinkler node included a standard microsprinkler emitter, latching solenoid valve, and control circuit with a master computer connected to each drip line controller using a wireless modem. Large or small valves can be installed according to tree size to allow a unique schedule to match differing water and nutrient requirements to accommodate replants, disease, growth, or seasonal changes. Data from electrical conductivity, pressure, soil moisture, or flow sensors could be installed to allow closed-loop irrigation and fertigation control. More recent work used wireless mesh networks for remote control of the individual nozzle system as illustrated in Figure 4.4 (Coates and Delwiche, 2008).

4.5 Irrigation requirement

The factor most limiting precision irrigation is lack of production functions that guide the timing and amount of irrigation within a field (Sadler et al., 2007). While the system of Coates and Delwiche (2008) can remotely control irrigation for an individual tree, it cannot determine the crop water needs for every tree in a given orchard. The science and practice of irrigation scheduling are well known and apply to precision irrigation. What varies is the spatial scale at which irrigation scheduling is applied. If the production goal in irrigating specialty crops is to maximize both crop yield and quality, then irrigation should be guided by the water requirements of a crop. The value from precision irrigation is realized by matching irrigation rates to variable crop water need within a field.

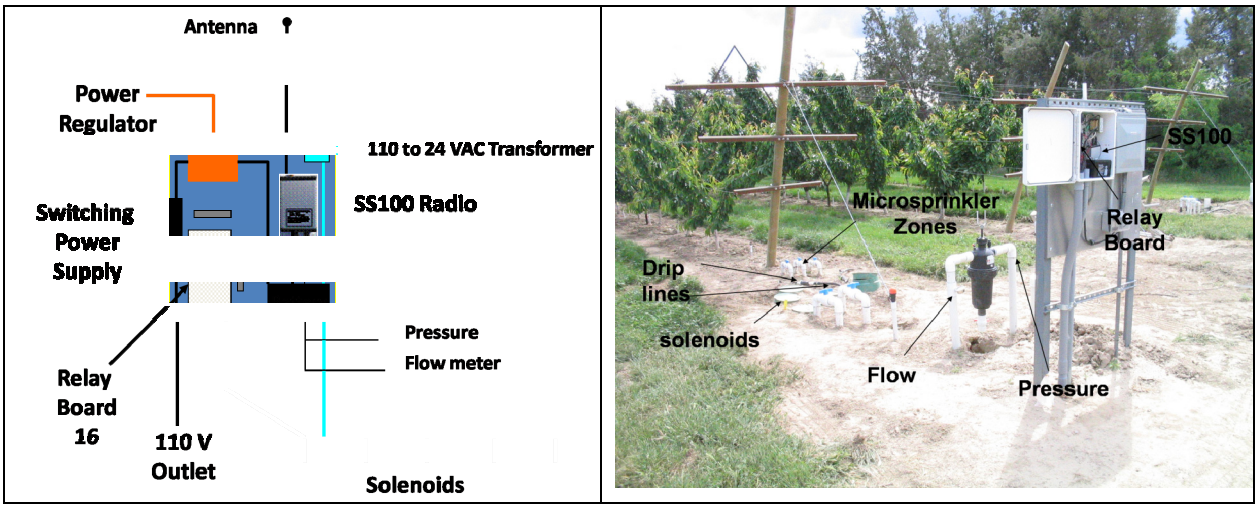

Figure 4.3: Remote real-time monitoring and control system for a combined drip and microsprinkler irrigation system in a research orchard in Washington State (Pierce et al. unpublished).

Figure 4.4: A wireless mesh network for remote control of the individual nozzle (personal communication Coates and Delwiche, 2010).

Variable water demand is created when factors that regulate water availability to plants vary in space and time and or when a field contains plants with different requirements due to stresses, age differences, genetic variation, and other factors. A pear orchard block, for example, can contain trees of different size or condition due to age, variety, or root stock, that have different water requirements. A frost damaged orchard may have a range of fruit load on the trees. A given field may have different soils with a range of water holding capacities and over time have different irrigation requirements depending on the weather. The conundrum for precision irrigation is the temporal variation in spatial variability. This may explain the lack of production functions cited by Sadler et al. (2007).

A potential solution to this conundrum is the development and use of effective tools that accurately estimate the crop water need site-specifically and in real-time. The next generation of precision irrigation technology will likely include real-time monitoring of plant and soil water conditions with wireless sensor networks feeding data to crop simulation models or other decision support systems that specify crop water needs by location within the field. A good example of emerging technology is the system developed by Oshaughnessy and Evett (2007, 2008) that varies irrigation rate based on leaf temperature. Their system uses wireless infrared thermometers mounted on center pivot irrigation arms as well as in the field to help determine whether to skip watering parts of a field because plants are suffering from disease rather than drought or because no plants have survived in that part of the field. Real-time or near real-time methods of assessing crop water needs may be the future of precision irrigation.

4.6 Remarks

A value proposition is what the customer gets for what the customer pays (Wikipedia contributors, 2008). It is clear from our discussion that the technology to remotely monitor and control irrigation is available, operationally effective, and increasingly affordable. However, the value proposition for precision irrigation, although seemingly intuitive, is not well defined. Warren Buffett is quoted as saying “Price is what you pay. Value is what you get" (http://hubpages.com/hub/Warren-Buffet-Quotes). Today, while the price of precision irrigation may be definable; the value, however, is not. Sadler et al. (2005) and Lu et al. (2005) conclude that so far, the research has proven that the equipment can be built to do precision irrigation, but economics are not favorable under current prices and costs. A large gap in knowledge about the production functions for a given site-crop-environment scenario is largely unknown and remains the biggest obstacle for precision irrigation (Sadler et al., 2007). Almas et al. (2003) conclude that feasibility of precision irrigation depends on field variability, crop value, economies of scale, and useful life of the equipment but suggest that prospects for precision irrigation were positive for Texas agriculture. Milton et al. (2006) reported costs for commercially available precision irrigation systems exceeded $21,000 and that cost-share is critical to the adoption of this technology. Intuitively precision irrigation is often perceived positively in terms of improved water use efficiency and increased yield when it in fact can have negative impacts on crop yields and the soil ecosystem. From their economic analysis, Feinermanz and Voet (2000) suggest that utilization of site-specific farming and adoption of improved irrigation and/or cultivation technologies do not guarantee water savings. Using a crop simulation model, DeJonge et al. (2007) concluded that precision irrigation showed slightly lower yields than scheduled uniform irrigation in a scenario where supplemental irrigation was valuable in only one of 28 years in Iowa corn production. Oliveira et al. (2004) reported that for tomato production in Tennessee, uniform management required 20% more applied water compared with site-specific management. Raine et al. (2007) estimated that 10% of the irrigated land

area within Australia could be adversely affected by root zone salinity resulting from the adoption of precision irrigation. They attribute this problem to a lack of understanding of all aspects of the whole system and significant knowledge gaps in many factors associated with precision irrigation decisions.

The reality is that precision irrigation is technologically feasible but remains primarily a topic for research. Conceptually, it makes sense to vary water application in ways that accommodate variable growing conditions across a field (Evans and Sadler, 2008). The key is accurate knowledge of the production function for site-specific water management. Perhaps real-time sensing of the soil-crop-atmosphere continuum across a field will adequately predict site-specific irrigation amounts and frequencies. Clearly, much more field experience with precision irrigation across a broad range of soils and crop production systems is needed before the full extent of its value proposition to farmers and to society can discerned.

The value proposition of precision irrigation remains largely undocumented. This may relate to the limited adoption of precision irrigation, although little data exists on the level or rate of adoption. However, the factors that favor precision irrigation remain, particularly the inability of agricultural producers to control inputs in ways that accommodate variable growing conditions across the field (Evans and Sadler, 2008). Because precision irrigation is a knowledge based management practice, the need is great to fulfill the knowledge gaps that currently limit its use in commercial agriculture, whether those gaps are lack of production functions (Sadler et al., 2007) or fundamental water flow in soils (DeJonge et al., 2007).

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Section 4. Precision irrigation

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5 Precision Application of Nutrients on a Site-specific Basis

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5.1 Introduction

Though farmers are operating on a personal farm scale, each of them is an integral and sensitive part of the global food security and food safety scheme. As such they do take responsibility not only for food production, but are also liable for use of resources and minimum interventions into the environment, for instance, by implementing codes of Good Agricultural Practice (GAP) through controlling nutrient surpluses and deficiencies on field level by applying the concept of balanced fertilization. This practice leads to the treatment of soils on their smallest scale of significant variability, i.e., site-specific nutrient management (SSNM) to realize the ambitious goal of minimum use of resources and impact on the environment.

In US agriculture, 28% of the total energy expenditure is for fertilizers (Miranowski, 2005). The total expenditure, which includes costs for fertilizers and pesticides, on an average is two times higher for specialty crops such as fruits, vegetables and nursery than for cereals, cotton and soybean (Miranowski, 2005). An indicator of excessive fertilizer application rates is the measured non-point nutrient losses to the environment. Eutrophication by nitrogen and phosphorus is a global problem, which affects both surface and marine waters equally. Both nutrients are of prime interest for balanced fertilization that matches their small-scale variability in the soil with exclusively demand-driven nutrient inputs (Haneklaus and Schnug, 2006).

Agriculture can be at conflict with nature conservation, irrespective of the land use system; SSNM, however, provides a scientific and technical basis to bring more balance to agricultural and environmental demands. One of the main reasons for the low adoption of SSNM technology is the inadequate economic return on the investment (Haneklaus and Schnug, 2006). In the face of climate change concern and depletion of fossil fuels, not only the local products with only short routes of transport, but also production techniques that utilize resources efficiently will become increasingly relevant (Lee et al., 2008). Farmers who implement Precision Agriculture (PA) technologies will meet both demands by reducing energy inputs for instance through coordinated, cost-effective field traffic and by reducing non-point nutrient losses through SSNM strategies.

It is the aim of this section to update advances in the field of site-specific nutrient management and to introduce new visions for future research and today's agriculture.

5.2 Capturing the variability of soil and plant nutrients

Soils are characterized by a four-dimensional space-time structure; monitoring of the associated variation of soil features is essential for optimizing land use in a sustainable way. A major and persisting obstacle for the reliable determination of the spatial variation of soil characteristics on a large scale is the expenditure for data acquisition.

The capacity of plants to extract nutrients seems particularly pronounced for macro nutrients and balances partly the effect of spatial variability in these nutrients. This is reflected in measured ranges of semivariograms that can be more than twice as long for plant features compared to soil features (Gassner, 2003). This equals a fourfold lower sampling density for grid sampling of plant material compared to soil material. These general and basic relationships may prove to be relevant when defining management zones. For example, an elevated nitrate content of vegetable crops is primarily a problem of an excess N supply. Maximum permitted nitrate levels in lettuce according to European Commission Regulation (EC) No. 563/2002 vary between 2,500 - 4,500 mg/kg (f.w.), depending on season of cultivation and cultivation practice (Santamaria, 2006). SSNM may provide added value for vegetable products by reducing the nitrate content efficiently: management zones are selected so that they reflect zones differing in plant available soil nitrogen supply; the nitrate content in the vegetative plant tissue, determined by rapid tests, might serve as a control tool for adjusting fertilizer rates. Another powerful option to adapt SSNM to farm conditions comes from the results of a combined field and state's survey (Haneklaus et al., 1998). Optimum nutrient ranges for an individual field were compared to those derived from surveys of sugar beet fields in three neighboring provinces by employing *BOLIDES* (*BO*undary *LI*ne *DE*velopment *S*ystem) for the interpretation of soil analytical data (Haneklaus et al., 1998; see below). The range of variation and the coefficient of variation of soil parameters were distinctly higher in the survey data, but optimum nutrient ranges were similar though somewhat lower for plant-available phosphate on field level. Such reliable assessment of critical nutrient ranges was shown to provide the highest potential for fertilizer savings when compared to normal practice of following universal recommendations (Haneklaus and Schnug, 2006). These and other data reveal also that *BOLIDES* is a reliable tool to assess critical nutrient values and ranges for the soil and plant nutritional status on field and regional scale (Schnug and Haneklaus, 2008).

The availability of a nutrient is governed by two factors, its chemical speciation and mobility, which is linked to the first factor. Soil testing for plant available nutrients is discrete in space and time and thus does not reflect dynamic changes between different nutrient pools. For a balanced and site-specific fertilizer input, however, it is critical to evaluate all available nutrient pools that may contribute to the nutrition of the plant. Gassner (2003) defined spatial speciation as the chemical reactivity of a nutrient with site-specific environmental factors, and the subsequent formation of geochemical species that display different spatial dependencies. In the Gassner studies, multivariate geo-statistical analysis was successfully applied to assess local functions of spatial speciation of phosphorus in soils: the readily, reversibly and sparingly available phosphorus pools were reproduced by variations in soil texture, soil type/equifertiles and landscape characteristics (Gassner, 2003). It can be expected that the prognosis of changes in the chemical speciation and equilibrium distribution of nutrient pools in relation to land use including fertilizer practice, geomorphology, and soil type will substantially improve the adaptation of site-specific fertilizer strategies.

A perfect solution to overcome the problem of data acquisition in sufficient density seems real-time sensing of the plant nutritional status, for instance by directly measuring the spectral signature of the reflection of crop canopies. Sensors can instantly deliver data in sufficiently high density at comparably low costs that are, for example, directly transformed into a change in the mean nitrogen fertilizer rate. However, these sensors have one very serious problem in common: changes in the spectral signature are related to numerous factors that directly interfere with the measurements and any use of the data without proper ground truth for calibration and verification must be avoided (Haneklaus and Schnug, 2006). What appears to be a setback for SSNM, might in fact be an advantage as fertilizer rates can be adopted significantly more stringent if the risk of miscalculation can be excluded by validating results. It might be suggested at this point that sensor-based variable rate application of nitrogen fertilizer rates avoid imperatively the risk of yield losses and thus an insufficient nitrogen supply so that any variation of the nitrogen rate blurs in background variation of plant available nitrogen in the soil.

5.3 Influence of small-scale variability of soil and plant nutrients on crop yield

Critical plant nutrient values are dependent on crop type, yield level, sampling date, and sampled plant part and chemical form of the nutrient. Soil samples can be taken throughout the year, but for comparison of soil and plant analysis the same sampling date and location is recommended. Critical nutrient values/ranges are the nutrient content levels above which soils or crops are sufficiently supplied for achieving the maximum potential yield or yield reduced by 5, 10 and 20 %, etc. A comprehensive overview of crop-specific sufficiency ranges for plant nutrients was presented by Reuter and Robinson (1997). However, an exemplary compilation and attribution of individual data and their evaluation revealed ultimately for sulfur response trials that it is not possible to assign a general validity of critical nutrient ranges, let alone threshold values. This observation is not only true for individual crop plants, but also plant families (Haneklaus et al. 2006).

The main drawback of transferring popular soil analytical thresholds and optimum ranges to management zones is that calibration against crop yield is based on a limited number of experiments at selected locations and sampling without reference to spatial autocorrelation (Haneklaus and Schnug, 2006). In addition, common procedures for calculating critical nutrient ranges do not take into account the non-linear relationship between growth factors and yield as postulated by *Mitscherlich* equation. Upper boundary line functions overcome all mentioned deficits of alternative methods (Schnug and Haneklaus, 2008). Thus, critical nutrient values can be verified on different scales, from individual field/farm layer to regional level (see Figure 5.1). PA technologies, geo-referenced yield monitoring and soil/plant sampling provide the data to generate boundary line functions. The boundary lines describe the highest yields observed over the range of values measured for the soil/plant nutritional status. Therefore, they describe the ‘pure effect of a nutrient’ on crop yield under *ceteris paribus* conditions. With BOLIDES it is feasible to calculate upper boundary line functions by well defined mathematical routines (Schnug and Haneklaus, 2008). The optimum nutrient value and ranges are determined by standard mathematical procedures (Schnug and Haneklaus, 2008).

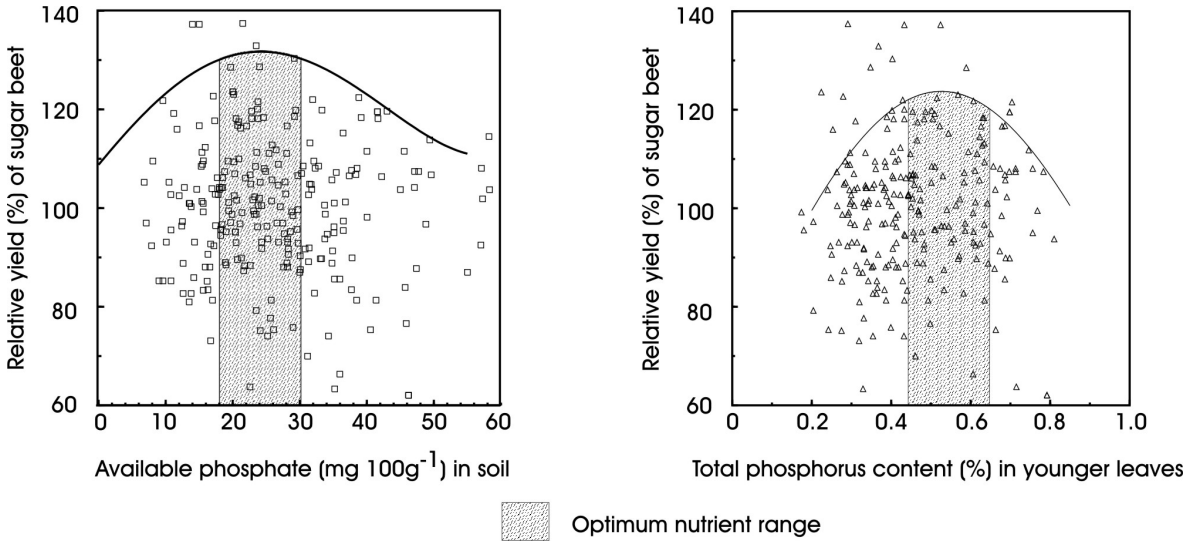

Figure 5.1: Upper boundary lines calculated by *BOLIDES* for the derivation of optimum nutrient ranges of (left) plant available phosphorus content in soils extracted by calcium-acetate/calcium-lactate (CAL) and (right) total phosphorus concentration in younger, fully differentiated leaves of sugar beet at start of row closing.

Boundary lines reveal that limitation of the nutrient supply is seldom the reason for reduced yield, particularly on production fields in intensive agricultural production systems (Fig. 5.1). Other non-adjustable factors as for instance climatic conditions (water supply) and biotic factors (fungal infections, infestation by pests) seem to significantly outweigh fertilizer input. In comparison, in extensive systems with restricted access to fertilizers it seems reasonable to rank individual nutrients according to their strength in reducing yield following *Liebig*'s 'Law of the Minimum' (Black, 1993). The routines of the PIPPA software package execute this task for plant analytical data (Schnug and Haneklaus, 2008).

The response to different fertilizer rates is measured by the increase in the nutrient concentration in the plant tissue and its impact on crop yield and quality. The spatial variability of soil characteristics, which influence the chemical and spatial speciation of a nutrient, will cause treatment contrasts (see above). Different experimental designs were tested on field scale for determining the influence of SSNM on crop yield such as management zones and continuous SSNM (for detailed information see Pringle et al., 2004a). Yield mapping permits an easy and instant way of retrospective analysis of tested fertilizer strategies and usually employs standard statistical procedures. Another option is the whole-of-block approach, which provides an alternative, powerful opportunity to adjust SSNM to prevailing environmental and production constraints. In comparison with other experimental techniques, whole-of-block experimentation uses geo-statistical procedures for estimating the influence of different treatments in adjacent blocks on target parameters (nitrogen status, crop yield) whereby constant ratios are tested against the background soil variability (Pringle et al., 2004b; Bishop and Lark, 2006). Standardized ordinary co-kriging predicted treatment responses and contrasts are the best (Bishop and Lark, 2006). The validation of treatments effects is favored by a high number of replicated test blocks within the training area and minimum distances between treatments (Bishop and Lark, 2006; Panten and Bramley, 2007).

5.4 Mapping the variability of soil nutrients and soil amendments

Geo-coded mapping of the spatial variability of soil and crop features is a requirement for any strategy involving SSNM (Figure 5. 2). The first step is data acquisition that reflects the spatial variation of the soil and plant nutrient status in a resolution that is ideally equal or higher than what variable rate technology (VRT) can transcribe if operating in a continuous mode. The highest resolution potentially managed site-specifically is the pedon (a homogenous three dimensional section through the soil profile of 1-10 m^2 surface and up to 2m depth in relation to the geogenic variability (Schroeder, 1978)). This premise of a sufficiently high data density for mapping is given for instance by grid soil sampling, which is costly and not viable in practice (Figure 5. 2).

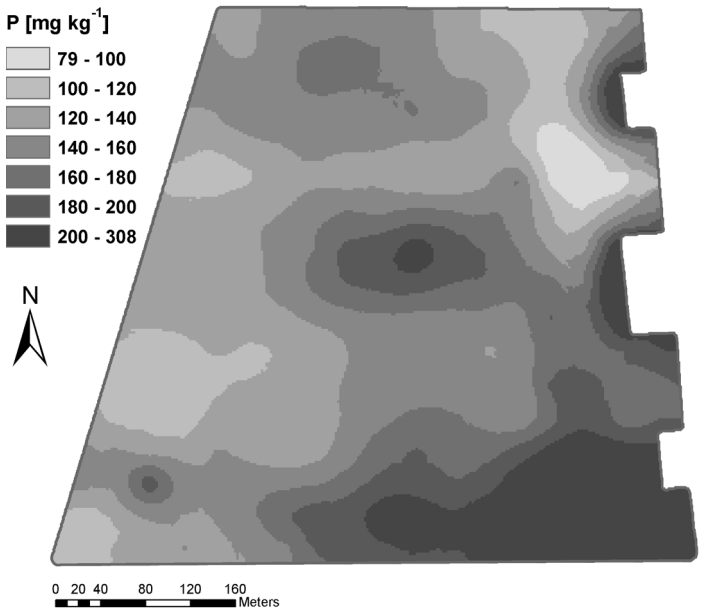

Figure 5. 2: Small-scale spatial variability of the plant available phosphorus content (mg kg-1) in soils extracted by calcium-acetate/calcium-lactate (CAL), determined by grid soil sampling at distances of 30 metres on a Fluvisol in northern Germany (52° 33' N; 9° 28' E). [Underlying semi-variogram model: spherical; range: 131.3 m; nugget: 327.8; sill: 985.04]

Co-kriging was shown to be practicable for reducing expenditures by decreasing the number of costly laboratory analyses in favor of cheaper methods. Co-regionalized variables can be, for example, clay and water content of air-dried soil (Kerry and Oliver, 2005), or infiltration rate and sub-soil bulk density (Ersahin, 2003). Before mapping correlations between co-regionalized variables need to be established on a site-specific basis. Moreover, similarity of ranges of semi-variograms and cross-semivariograms must be verified for each pair of variables (Ersahin, 2003; Figure 5. 2). When using sensor data it might be necessary to repeat geo-statistical analysis after each measurement if figures are not constant over time.

Another alternative is autonomous soil sensing systems, but metrological specifications do not permit the correction of interferences with other variables and thus confine analytical precision and reproducibility (Haneklaus and Schnug, 2006; Ortega et al., 2008). Consequently calibration against soil analytical data is inevitable (De Gruijter et al., 2008). De Gruijter et al. (2008) compared different approaches for the localization of sampling points that allow for generating high-resolution soil maps. These strategies are constructive where no soil inventory and other geo-referenced soil and crop information is available; in all other cases so-called monitor pedo cells (validated sampling locations, pedons, which reflect the whole range of spatio-temporal variability of soil and crop features) which have been selected from directed sampling points proved to be apt for this task (Haneklaus and Schnug, 2006; Lin, 2006; Ortega et al., 2008). The current status and application spectrum of digital soil sensors for precision agriculture have been compiled by Viscarra Rossel et al. (2008).

Recapitulating, it can be stated: mapping must include quality assurance procedures. For the best perspective for decision-making and effectiveness of SSNM the need for high quality maps cannot be overstated.

Historically, farms which implemented precision agriculture technologies in continuous mode are only found sporadically, while commonly site-specific, uniform fertilizer rates are implemented for distinctive management zones. This implies averaging of variability. Retrospectively SSNM has been evolved originally to map and merge small-scale variability with an exclusively demand-driven variable rate input of nutrients. The superior effect of this approach lacks proof until now and the capacity of crops to adapt to different growth conditions (see above) seems to justify a controllable number of management zones. Management zones, which depict crop productivity levels can be delineated on the basis of directed sampling, yield maps, geomorphology, remotely sensed images and local knowledge of the farmer (Pringle et al., 2004a; Fleming et al., 2000; Haneklaus and Schnug, 2006; Ortega et al., 2008).

5.5 Technologies to precisely apply nutrients and soil amendments

Nutrients and soil amendments are available in gaseous, liquid, solid, and granulated form. They are soil and foliar-applied using different technologies; in irrigated farming, fertigation is common practice. Here, nutrients are partitioned through irrigation systems. Section 5.4 covers technologies to precisely apply water and any strategy for SSNM suggested in this section needs to be synchronized with spatially variable irrigation opportunities discussed in that section.

VRT needs to be implemented for SSNM to adjust the rate by either a prescription map, which is created by the user integrating yield, soil, topography, remote sensing, plant and local knowledge data, or from information recorded by sensors in real-time. Stewart et al. (2005) compared and appraised sensor-based and map-based VRT systems.

Specialty crops such as fruits provide the best option for SSNM from the viewpoint of economic return, but the development of PA machinery has thus far focused on cereal and other field crops so there is a need to develop appropriate technologies. Increasing efforts can be seen to develop technology for fertilizing fruit trees, which varies the fertilizer rate in relation to tree size employing ultrasonic sensors (Schumann et al., 2006) or laser light detection and ranging sensors (Escolà et al., 2007).

Generally speaking three major sources of errors exist when performing variable rate fertilizer application: (i) accuracy of the application map, (ii) accuracy of navigation, and (iii) accuracy of the application technology. The most common technology for site-specific fertilizer applications are granular applicators equipped with VRT. Fulton et al. (2005a) compared the accuracy of two spin-disc spreaders and two pneumatic applicators by uniform-rate tests. Various potential distribution pattern inaccuracies were detected such as asymmetry in patterns and high deviations from the mean and pattern shifts. Fulton et al. (2005b) further investigated the delay and transition times for the applicators and found that newer systems performed rate changes quicker because of advancements in hydraulic control valve technology. The major conclusions drawn from both experiments were the need for proper calibrations to maintain acceptable performance of VRT and a standard testing protocol for VRT applicators (Fulton et al., 2005a; 2005b). Chan et al. (2004) modeled absolute error maps and concluded that the compensation of machine delay times and the availability of an accurate GPS receiver are most important, while sampling frequencies seem to be of minor relevance. Decreasing the operation speed can reduce the magnitude of error in system control. This will be economically viable only if fertilizer application becomes an automated process carried out by robots.

VRT nutrient application has always been seen as a possibility to decrease the negative impacts on water quality caused by fertilization. Although it is intrinsic that SSNM reduces adverse environmental impacts, hard evidence has been rarely found. Harmel et al. (2004) monitored the surface runoff and water quality of two fields, one under uniform and the other under variable rate fertilizer regime in a paired watershed study. The results were not consistent although the authors found some indications that VRT nutrient application bears the potential to improve water quality.

A similar shortcoming that needs to be overcome is an improvement of economic gains. Robertson et al. (2007) calculated a potential economic benefit for Western Australia grain growers of <5 A$/ha to over 40 A$/ha, but these figures can not be readily transferred to other regions and continents. Bullock and Lowenberg-DeBoer (2007) and Rajsic and Weersink (2008) proposed to utilize on-farm experimentation for setting up site-specific yield response functions and evaluating the expected profitability of VRT. Under current production preconditions this is strongly influenced by the spatial variability of soil nutrients and potential yield, significant improvement of product quality and potential fertilizer savings, and at any rate, the final decision for or against the implementation of the technology is dictated by market prices. The situation may change under the conditions of climate change and decline in fossil fuel supplies and a corresponding increase in cost. Then, fertilizer and pesticide inputs may become less available, or at least much more expensive, leading to reduced applications and a potentially negative impact upon crop yields (Lee et al., 2008) if not counterbalanced by SSNM. In addition, farmers who implement SSNM technology on a timely basis can optimize field traffic to apply resources on the farm.

5.6 Remarks

Compared to concerted recommendations, on-farm experimentation offers the biggest chance to improve SSNM and nutrient utilization efficiency by generally exploring and instantly adapting the best site-specific treatments to prevailing growth conditions. This will intrinsically improve crop productivity and crop quality. Any strategy for SSNM should take GAP codes fully into account.

Dynamic maps could be a real breakthrough for forecasting insect gradation and rating of disease indices. Here, indicator kriging offers the possibility to predict nutrient-related disease indices (Salac et al., 2004), which can be integrated into SSNM and pest control. With a view to standard site-specific fertilizer applications dynamic maps seem to be particularly superior in situations of acute and severe nutrient deficiency, which impair crop yield if not compensated by timely fertilization.

Ongoing nutrient losses to water bodies are a major threat for drinking water quality and eutrophication. This fatal condition needs to change on a global scale. SSNM offers a realistic prospect to counteract the problem on a voluntary basis before regulatory measures such as taxes and penalties are introduced, which outpaces any required investments for the technology.

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6 Precision Application of Chemicals on a Site-specific Basis

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6.1 Introduction

Chemical application for weed and pest control in agricultural production systems continues to be of great interest within society due to increased concerns over environmental protection and the potential for pesticide residue in food. Concern regarding agricultural chemical residues in the environment is not unfounded as independent and federal sampling programs have documented their presence. Estuarine locales, for example, in Northern California have been found to contain spray residues that coincides with dormant spray applications in the winter (Werner et al., 2004; Brady et al. 2006; Viant et al., 2006).

These concerns have increased research activities focused on developing site-specific precise application techniques for chemical spray applications in all sectors of the agricultural community. Research activity over the last several decades has been reviewed in recent years regarding electronics for agricultural equipment (Stone et al. 2008), agricultural chemical application (Bode and Bretthauser, 2008), pesticide application (Giles et al., 2008), site-specific management of plant parasitic nematodes, crop diseases and weeds (Bjerre et al., 2006; Dunn et al., 2006; Gerhards and Christiansen, 2006) in addition to in depth discussions on vision sensing requirements (Brown and Noble, 2005) and robotic weed control systems (Slaughter et al. 2008b).

Many of the ideas and information presented in preceding chapters will not be duplicated within this discussion; however, some overlap is inevitable. This review on site-specific precision applications will discuss general concerns with weeds, review weed sensing using real-time vision systems and general optoelectronic sensors, concerns with real-time identification of crop diseases from fungi and parasitic nematodes and recent activity with insect monitoring. Additional discussions will focus on variable rate applications, use of prescription maps and real time control for site specific chemical applications. Several research developments within these realms will be presented.

6.2 Sensing weeds

One of the primary non-selective herbicides used within the agricultural community world-wide is glyphosate (N-(phosphonomethyl) glycine). It is likely the most economical pesticide used due to its ability to control a broad spectrum of weeds under many conditions (Baylis, 2000). Economics aside, yield losses still occur due to weed infestations in many cropping systems and some estimates have placed annual losses at approximately $4.1 billion due to weeds in the U.S. alone (Anglund and Ayers, 2003).

Although weed patch stability mechanisms are generally unknown, some ideas regarding their stability have been discussed by Gerhards and Christensen (2006). One concept is that post-emergent herbicide efficacy is low when applications are made to high density weed patches due to variable spray penetration within the weed patch canopy. Another idea is that persistent weed populations may be due to weed seedlings emergence after spray applications for weed control. The stability of weed patches suggests that mapped weed distributions are good predictors of future distributions (Gerhards and Christensen, 2006).

Manual hand hoeing to remove weeds from specialty cropping systems, especially areas within the seed-line, can be up to five times the cost of conventional cultivation techniques (Slaughter, 2008a). Gerhards and Christensen (2006) indicate that mechanical weeding and prophylactic practices have decreased over the last several decades since post-emergence herbicide is often used. However, herbicide use has not eliminated weed problems in agriculture and the need for manual weed removal is still an issue within specialty crop systems, particularly during the first several weeks of crop emergence when competition for resources is greatest.

6.2.1 Optical and vision systems for weed sensing

Slaughter et al. (2008b) presented an extensive review indicating how in-field machine vision weed detection and identification with concomitant variable field conditions (e.g., soil color, wind, plant color and shape, water or nutrient stress or tissue damage) may be the greatest challenge for automated weed control. They note that leaf occlusion remains a challenge for weed detection systems relying on shape recognition. Real-time machine learning for on-the-go weed discrimination from crop plants is still in its infancy. The literature is dense with respect to research for classifying weed/crop signatures over the years and much of the research requires off-field post-processing of images. Recent studies, i.e., studies conducted in the last decade, will be emphasized in this review.

Research by Blackshaw et al. (1998) evaluated the “Detectspray” system over a three year period. A conceptual view of the “Detectspray” system is given in figure 6.1. Weed detection was greatly reduced during early dawn and before dusk (as per warnings from manufacturer). They determined that a tall dense crop stubble resulted in limited detection of small weeds unless their density was high (70 plants/m^2). Additionally, detection varied with weed species and some weeds required greater surface area for adequate detection and spray (consistent detection occurred with 3-4 leaves on broadleaf species while grass weeds required five to six leaves for adequate detection and spray). However, reports (Ragan, 2009) have indicated that for green spraying against a soil or non-green background, ground area scanned is 20 x 60 cm and ground speeds are possible up to 16-20 km/h with a 5 cm diameter resolution for actuating spray. Blackshaw et al. (1998) indicated that the system is inappropriate for selective control of weeds in crops, however, could be used as a pre-field preparation prior to planting or to control recurrent weeds on fallow land. They reported spray savings between 30-70%.

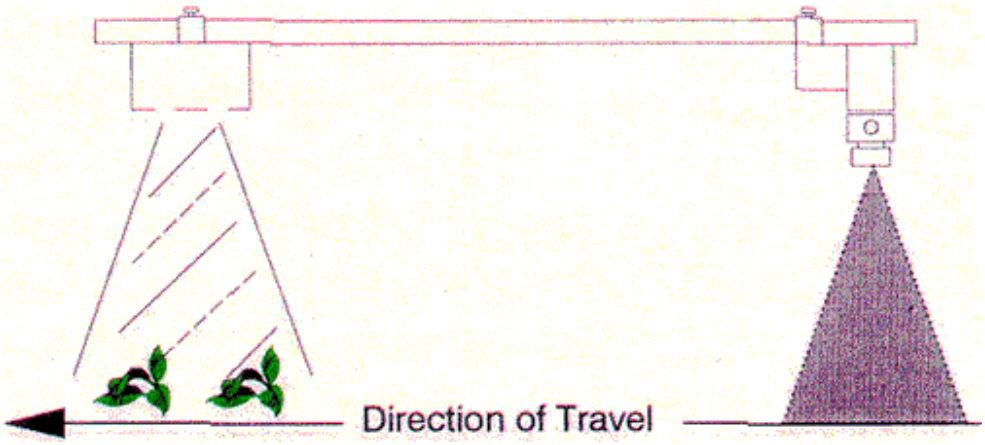

Figure 6. 1: The "Detectspray" system with sensor on left of figure for identifying green plant tissue and spray application shown on right (from Ragan, 2009).

Baylis (2000) reported on research from the mid-1990's that used differential reflectance of red and infrared wavelengths between green plant tissue and soil background. Sun angle was a factor in weed detection. The system required slow movement through the field and additional requirements to drive spray equipment slow within the field may limit advantages.

Noble and Crowe (2001) developed classifiers for identifying differences in six weed species using diffuse reflectance ultraviolet-visible-near infrared (UV-VIS-NIR) wavelengths. The methods developed were at least 90% effective in identifying species based on three to five wavelength characteristics of the respective species. These researchers indicated that fast discrimination of weeds from other plant species for site specific herbicide applications continues to require study and development and, although in-situ field work is needed and should be pursued, additional work is needed for further understanding of leaf spectral properties for plant discrimination from weeds and background properties. NIR reflectance imaging should not be overlooked due to challenges in field implementation since it may provide important information about plant health and other crop management issues.

Yang et al. (2002) attempted to use an artificial neural network (ANN) to recognize maize and several weed species from grayscale images. The work was based on images captured in the field and post-processed in the lab. They concluded that it was "very difficult for ANNs to precisely categorize a specific plant species" as the success rate of a single-stage ANN in distinguishing maize and four weed species from each other never exceeded 40%. A multistage ANN was shown to increase the success rate for distinguishing maize from weeds from 66% to 82%.

Downey et al. (2004) implemented a digital video system for continuously mapping weed patches within the seed-line of row crops. The system allowed weed location descriptions within centimeter scale accuracy when coupled to RTK-GPS (Figure 6. 2). The system had an accuracy of 85% using off-field post-processing for identification of weed versus crop. Multi-year images from the same fields could verify localized, returning or migrating, weed infestations that could be used as one input for site-specific agricultural spray applications (Downey et al. 2004).

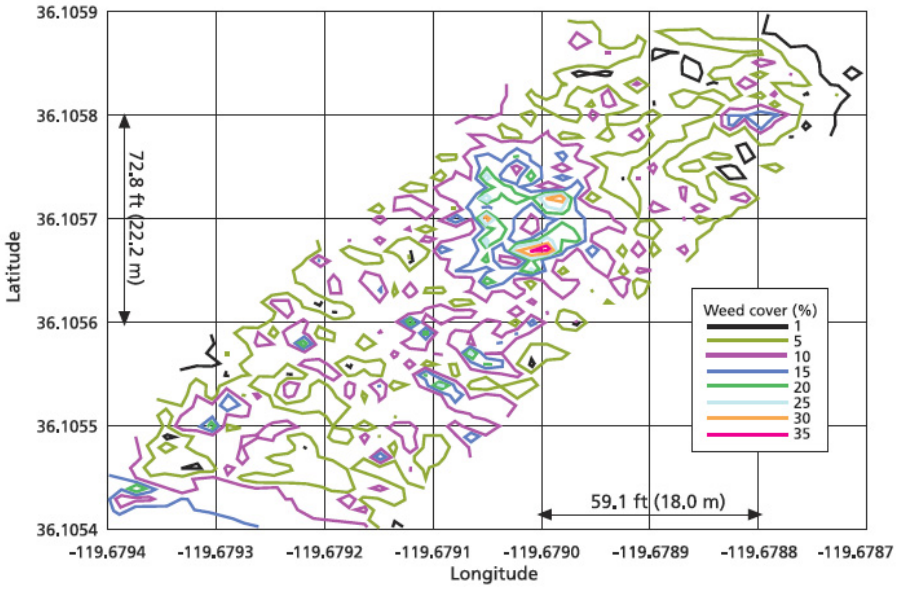

Figure 6.2: Automatically generated high-resolution map showing the spatial distribution of weeds in a cotton field (from Downey et al., 2004).

Early work by Slaughter et al. (2004) discussed weed discrimination in field processing tomatoes and used specific spectral bands (optical absorbance regions and narrowband hyperspectral ranges) that resulted in 95-100% accuracy in discriminating between weeds and crop. They also found that broadband color based models were only 75% accurate for weed discrimination.

Brown and Noble (2005) discussed and reviewed weed detection and identification for remote sensing and digital cameras along with limitations for reported weed identification systems. Typically, airborne remote sensing is only viable for dense and uniform weed patches with unique spectral characteristics. Color digital cameras/vision systems for ground-based identification use spectral analysis in addition to spatial/morphological features. They concluded that research needs still exist and should focus on artificial lighting, spectral band requirements unique to specific weed species, continued image processing and processor advancements, multiple spatial resolution systems and multi-perspective images.

Panneton et al. (2006) used induced fluorescence spectroscopy as a tool for real-time weed-crop discrimination. The system used a fiber optic probe, held 5mm above the plant leaf to collect the leaf fluorescence data. In a small study of potted maize and weeds the system showed good potential for distinguishing monocotyledon from dicotyledon species. However, the method was less effective when discriminating between weed species at the monocotyledon stage.

Schuster et al. (2007) captured field weed images on a sparse grid spacing (10m x 18m) with a digital color camera and no artificial lighting. They developed a plant discrimination algorithm off-field for identifying shape features and found the system identified 99% of dicotyledonous and 75% of

monocotyledonous plants correctly. The algorithm did not address leaf occlusion and the accuracy decreased with increasing weed density. Their semi-automated and automated system underestimated the weed density of weed patches in most cases due to leaf occlusion. Figure 6.3 shows weed maps they developed from manual, semi-automatic and automatic weed identification methods.

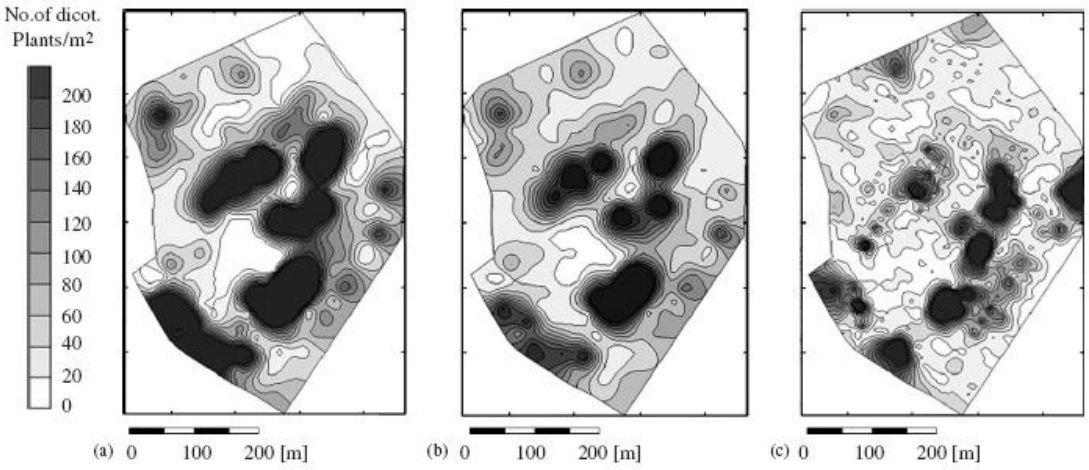

Figure 6. 3: Dicotyledonous weed maps developed from (a) manual weed mapping, (b) semi-automatic weed mapping and (c) automatic weed mapping (from Schuster et al., 2007).

Piron et al. (2008) used combinations of filters for detecting weed species within field grown carrots. Field images (an example is given in figure 6.4) were obtained with a black-white camera coupled to a multispectral device using a rotating filter wheel with 22 interference filters in the VIS-NIR domain. Their system for image capture is diagrammed in figure 6.5. Fifty-one images were captured during early growth of crop seedlings. Classification of carrot crop versus seven weeds species was 72% accurate when using a combination of three visible light band-pass filters. Slightly better results were obtained at advanced plant growth stages.

Slaughter et al. (2008a) studied the effects of identifying weeds in field grown lettuce and found that multispectral images of leaf reflectance in the VIS and NIR were able to establish a site-specific weed classifier to distinguish lettuce plants from weeds. Accuracies on the order of 90% were reported and resolution was approximately 3 mm diameter. Additionally, as opposed to some methods reported, field spectra samples were collected in real-time with the image acquisition system in motion similar to that required for automated weed control.

Figure 6. 4: Early growth carrot and weed competition (from Piron et al., 2008).

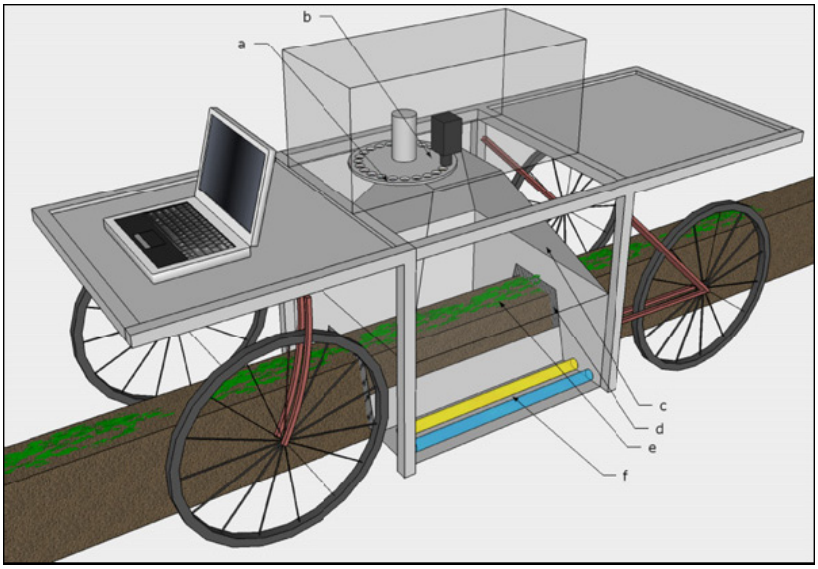

Figure 6. 5: Schematic view of image acquisition device (from Piron et al., 2008) for weed identification using twenty-two filters with annotated components (a - filter wheel and stepper motor, b - camera, c - reflector, d - brushes, e - carrot ridge line, f - lighting).

As these studies show, there are several ways to identify and classify weed locations within fields. However, identification criteria for specific weed types within fields or seed-lines is a much more difficult problem than basic optical sensing for green tissue or visual morphology of individual leaves or potted plants. The lack of standard testing criteria minimizes the ability for comparison between

studies which ultimately slows progress by limiting the framework that other researchers can build on (Brown and Noble, 2005).

6.2.2 Sensing plant pathogens and insects

Monitoring and tracking systems for invasive insects and fungal diseases that are detrimental to crop production systems continue to be manually assessed and scouted by farm advisors and pest management personnel. Current remote sensing methods cannot be used in diagnosis of diseases as other stress agents may lead to similar effects on canopy spectral reflectance (Bjerre et al., 2006) and the fact that most disease symptoms are highly variable according to pathogen strain, host cultivar and the environment.

Plant pathogens are estimated to cause yield reductions of up to 20 percent in the majority of cropping systems worldwide (Bjerre et al., 2006). Dunn et al. (2006) estimated that worldwide yield losses from nematode infestations were upwards of $77 billion annually. Yield losses depend on climate conditions and the susceptibility of the varieties grown, but crop rotation and other sanitation practices can also play a major role in reducing innoculum and delaying epidemic development. Fungicides are considered to be essential for effective control of plant diseases in many crops and today it is common practice to control diseases based on assessments of whether an attack of economic importance will develop (Bjerre et al., 2006).

Canopy spectral reflectance from aerial or satellite imagery may be capable of identifying diseased plants, however, a robust calibration for the range of crops, crop physiological conditions and measurement conditions encountered is required (Bjerre et al. 2006). Additionally, research into site specific management of plant parasitic nematodes through use of global position system (GPS) technology is in its infancy and for this technology to be used successfully in nematode management a general understanding of nematode biology, spatial distribution, and visible crop characteristics due to infestations is required (Dunn et al 2006).

Real-time sensing for nematode or fungal infestations has not been widely studied. Above ground symptoms are rarely, if ever, sufficient evidence to diagnose a root problem (Dunn et al., 2006). Sample analysis (laboratory assay of soil and or plant samples) is usually required to diagnose symptoms. When they are identified and their relative population densities are known, those data can be compared with experimental data and field observations to estimate whether the crop will be injured by that population under those conditions, and, in some cases, allow application of management tactics specifically suited to the pests (nematodes) found.

Bjerre et al. (2006) discusses a decision support system of fungicide treatment for plant disease, however, these criteria are generally focused on cultivar, growth stage, field observation, weather conditions, and the anticipated epidemic progress. Other than weather conditions, sensors do not exist that measure when fungicide treatments are required for plant diseases. Developing a less labor-intensive and mechanized or automated monitoring method for assessing disease level and subsequent control needs to be pursued (Bjerre et al., 2006)

GPS and geographic information system (GIS) technology could be a valuable management tool for nematode and fungal infestations and locations by correlating those data with other physical, chemical

and biological factors that can affect crops (Dunn et al., 2006). However, concerns about the limitation of using this technology continue. The cost of manually collecting soil and/or plant tissue samples, processing them in a lab to obtain the data needed for each point on a grid and providing an historical framework for the data is daunting to many researchers and farm managers. However, an automatic system for collecting and packaging soil samples for laboratory analysis is currently under development (AgRobotics, 2009).

West et al. (2003) discussed methods for identifying the spatial distribution of disease in fields that could be used to alleviate off-target spray applications. Many plant diseases result in optical property changes of the crops and these changes have been used for many years for disease risk assessment but are also time consuming and have inherent inaccuracies. West et al. (2003) indicated that diseases from pathogen propagules can be identified in the VIS range (similar to chlorophyll degradation), and photosynthesis disturbances can be identified in the fluorescence range. Also crop senescence, density and leaf area can be identified in the NIR range. Hence, optical changes have the potential for identifying and detecting disease presence. However, other plant stress factors can often produce similar NIR responses (Bjerre et al. 2006).

Tartachnyk et al. (2006) used laser-induced fluorescence to measure the effects from nitrogen deficiency and pathogen infestations; however, their research required in-lab analysis and was not a real-time sensing development. Results showed long term nitrogen deficiency and pathogen infestations had increased ratios of induced fluorescence at specific wavelengths. Additionally, the researchers found potential fluorescence differences for discrimination between nitrogen deficiency and pathogen infestation. While currently this application requires lab analysis time before predictions can be made regarding prescription maps or spray decisions, future research efforts may facilitate on board sensing in the field.

Chaerle et al. (2007) developed a combined thermal and chlorophyll fluorescence imaging system. They deduced that the combination of this dual imaging technology can highlight pre-symptomatic responses not observable in the visible spectrum and can be used to identify disease or plant stress. Lenk et al. (2007) discussed the use of chlorophyll fluorescence for detecting leaf diseases. Often responses to pathogen attack involve the accumulation of specific compounds, however, the methods described are all laboratory based and not yet possible for on-the-go field measurements due to instrumentation vulnerability to rough road/field conditions and sample preparation requirements.

Identification of insect infestations using harmonic radar for identifying insect flight paths has been discussed by Riley and Smith (2002). Recorded flight trajectories have shown previously unknown affects including foraging behavior and wind compensation. However, they list several drawbacks to this detection method including the requirement of a clear line of site between harmonic radar and insects, flat terrain required and detected targets must be within the range of the generated beam (generally up to 3 - 4 m). Other problems identified were ground radar echoes and vegetation clutter which masked the weak signals returned from insects.

Chapman et al. (2004) reviewed the use of radar technology in the tracking of migratory flying insects (aphid and other beneficial predators and foraging flights of beneficial pollinators). The techniques used “vertical looking radar” for monitoring high (aerial) insect migrations and a harmonic technique for low-altitude insect flights (several meters off the ground). They indicated that as computer processing

speeds increase it might lead to an ability to monitor continual heights (up to 1200 m) as opposed to fixed heights used in recent studies. Additionally, the harmonic option for insect monitoring continues to have some challenges since there are occasions when insects disappear from the detection system and it is unknown if these insects land on ground, plant tissue or have flown above the detection beam.

Garcia (2006) mapped *Helicoverpa armigera Hb.* (Lepidoptera: Noctuidae) from manual field surveys in a 20 ha tomato field. This method characterized insect spatial distributions with geostatistis, GPS and GIS. Grid spacings were 5 m by 5 m and ordinary block kriging was used to estimate insects at un-sampled locations. Examples of the maps developed are shown in figure 6. 6.

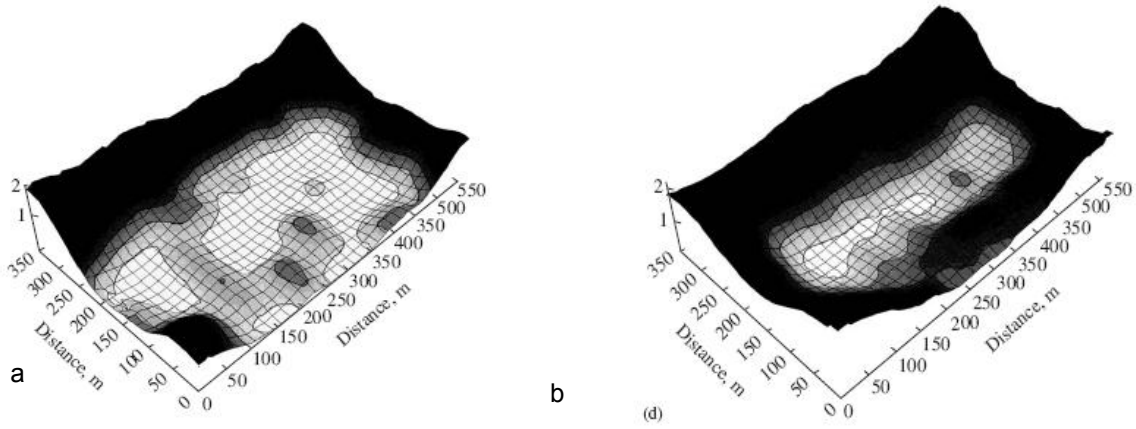

Figure 6.6: Initial distribution map (a) of *Helicoverpa armigera Hb.* and distribution (b) after eight days (vertical scale represents the natural log of insect density, from Garcia, 2006).

Johnson et al. (2007) discussed the difficulties in studying and discerning root feeding insects and the lack of empirical and theoretical conditions for developing monitoring frameworks. Their work discussed requirements for studying root-feeding insects with non-invasive techniques of X-ray tomography and acoustic field detection. X-ray tomography was used to study insects' movement within the soil and identify host-plant characteristics. Acoustic detection of soil insects has been used for management decision systems within the plant container and citrus industry. Once again this is a laboratory scale, or bench-top, experimental measurement technique that is far removed from on-the-go measurements where sensitivity of instrumentation during real-time movement under field conditions can be problematic.

Jiang et al. (2008) presented results on a remote pest monitoring system that trapped and counted pests (95% accurate) in real-time and transmitted environmental conditions (temperature, humidity, wind speed) and pest data using wireless communication technology. The system was tested for a one-year period and the researchers indicate environmental parameters and population dynamics of the organism of the study were adequately monitored giving managers the ability to judge and correlate climate conditions with the presence of specific pests. The researchers discussed future opportunities with these types of systems to monitor invading insects, use of a long-term data base for

integrative pest management and development of population dynamic models for assessing pest invasion and control strategies.

6.3 Site-specific spray applications

Bode and Bretthauer (2008) presented a conceptual review of the advances in spray application technology over the last two generations, including direct injection of chemical, on-board application control systems, air-assisted and electrostatic sprayers and nozzle development. These technological advances have resulted in the ability to precisely apply chemicals with minimal impact on the environment. Additionally, the basic method of chemical application over the years, for control of weeds and pests, has changed little due to two reasons: first, new technology is not consistently efficient in applying the multitude of pesticides available. The second reason is that operators do not use conventional equipment in ways that maximize efficiency of spray applications.

Bode and Bretthauer (2008) also discussed the differences between flat fan nozzles and pulse width modulation of the nozzle flow rate based on electronic control of individual nozzles that alters the duty cycle. Additional advancements, other than lowering the spray pressure to increase droplet size that minimizes drift, include reducing exit pressure of the spray as it leaves the nozzle by using a pre-orifice that restricts flow or internal turbulence chambers that absorb energy and reduce pressure of the spray exiting the nozzle. Standard, or conventional, spray controllers use pressure to vary nozzle flow rate and droplet size of the spray exiting the system. Pulse width modulation allows independent control of flow rate for each nozzle. An additional advancement, discussed by Bode and Bretthauer (2008), considers the difference between conventional nozzles with fixed orifices that can vary flow rates over a range of 2:1 and new variable flow rate nozzles with varying orifice sizes that allow pressure changes over a large range of flow rates with minimal changes in droplet size. Early research on variable flow fan nozzles discussed by Womac and Bui (2002) controlled turn down flow rates from 13 to 1, ranging from 0.23 to 3.0 L/min, at specific nozzle heights with concurrent control of droplet diameters based on the system pressure.

6.3.1 Variable application for chemicals

In an early study on variable rate applications, Al-Gaadi and Ayers (1999) evaluated a spatially variable rate application system with GPS/GIS interface/integration for site-specific applications. Soil type and organic matter content were used to indicate the appropriate rate of herbicide application for specific areas within the test fields. The authors developed a program to receive on-the-go GPS sprayer locations and retrieve the predetermined application rate from a previously developed GIS map corresponding to the current sprayer field position. Additional programming allowed changes to active ingredient on-the-go for the desired application rate at a specific sprayer ground speed and field position. Results indicted that delay times for direct injection were generally less than 1 s and application rate errors were generally less than 1% with excellent system repeatability.

It should be noted that the direct injection systems often discussed in the literature are actually systems that hold the carrier fluid (water) and chemical in separate storage containers and chemical injection is upstream of nozzle locations. For these systems “direct injection” is basically chemical injection into the carrier flow line. This is quite different than the direct nozzle injection systems discussed by Downey et al. (2006). Direct injection systems have the advantage of reducing chemical

mixing and compatibility issues (Bode and Bretthauer, 2008). Additionally, this minimizes clean up, disposal and operator exposure problems, and has the ability to give operators precision spraying capability at specific rates over specific areas. This has provided savings to the producer and has increased environmental protection.

Anglund and Ayers (2003) evaluated a chemical injection system (Raven SCS 750, Raven Industries, Inc.) for variable rate and pressure based applications with a separate carrier flow and chemical injection system. Details of the functionality of this system with GPS interfaced technology are briefly reiterated. Variable rate applications begin with GPS data received that indicate the position in the field with respect to the predefined application map and the desired predetermined application rate is sent to the injection controller for the chemical application rate. Pressure-based application rate changes adjust the carrier flow valve and sprayer speed for constant flow injection of chemical. The injector pump speed varies based on carrier flow and sprayer speed for constant application rates.

Anglund and Ayers (2003) evaluated the accuracy of constant and variable rate applications and the response time for chemical to arrive at the nozzle during variable rate conditions. However, variable rate application with chemical injection was not evaluated in the field and chemical injection tests were done with blue dye and manual time measurements once the system reached the desired pressure. They report that the time for a change in application rate to be realized by the system when moving into the next prescription map zone was 0.65 s based on the 3 s response time for the control system to predict the next zone criteria. The variable rate response time reported by this research was based on the time span encompassing the 10% to 90% injected concentration change after a step input to the controller. The average reaction time for these events was greater than 1 s with values observed up to 4 s. Additionally, injection lag times were measured from 15 -55 s for these systems. Pressure based lag times were within 2.35 s.

Giles and Downey (2003) studied the differences between conventional pressure-based control and blended-pulse control. Results showed that blended-pulse control gives operators better control over nozzle flow and droplet sizes (for environmentally sensitive area protection, that is, real-time mitigation of spray drift) with 3:1 changes in vehicle speed. Additional elements of their study showed spray drift control was possible when using on-board, and on-the-go, weather monitoring and sprayer location approach towards potential hazards. This study evaluated spray application for a variety of conditions: uniform application rate under varying speed conditions, variable application rate under constant speeds and drift mitigation while ambient conditions were monitored.

Vogel and Wolf (2005) adapted a conventional spray system for variable rate application of herbicides under site-specific conditions. Their study found that although weed patches were managed with commercially available variable rate technology, errors were found when prescribed rate changes were turned on and heavy spray residues were observed when the plant canopy interfered with the vehicle ground speed radar and thus application rate. However, variable rate applications generally provide herbicide savings. For example, the work discussed by Dammera and Wartenberg (2007) used a sensor-controlled sprayer for variable rate applications for late weed infestations and found 25% savings in herbicide with no yield reduction when compared to conventional applications.

Use of variable rate application for applying nematicides to crops is a relatively new concept and very little research is available to determine the logistic and economic potential for this technology.

However, Dunn et al. (2006) briefly discussed conventional versus variable rate nematicide applications and focused their discussion on sampling grid sizes for effective nematode population assessments prior to spray applications. Conclusions were that conventional and variable rate technologies were inconsistent for these applications.

6.3.2 Prescription map based chemical application

Qiu et al. (1998) in an early study of the effects of using GIS software for herbicide application maps, assessed applications for direct injection systems (on the spray platform and not directly at the nozzle). The results indicated that direct injection systems had application errors as high as 40%; generally due to desired changes in chemical concentrations at remote nozzles along the spray boom not occurring until 80 m of travel had occurred after the "electronic" request was initiated.

Exposito et al. (2004) developed temporal and spatial maps for *Convolvulus arvensis L.* in sunflower and used this data for precision herbicide spray applications. Weed density maps (7 m x 7 m grid spacings) were developed from kriging methods and isotropic variograms were used to estimate weed density and economic threshold requirements for spraying. Figure 6.7 shows the maps developed for estimating weed density and subsequent spray requirements. Results indicated that if the herbicide was applied only to areas that exceeded the defined economic threshold limit, in this case greater than 14 plants/m^2, average reduction in herbicide cost was approximately 81%.

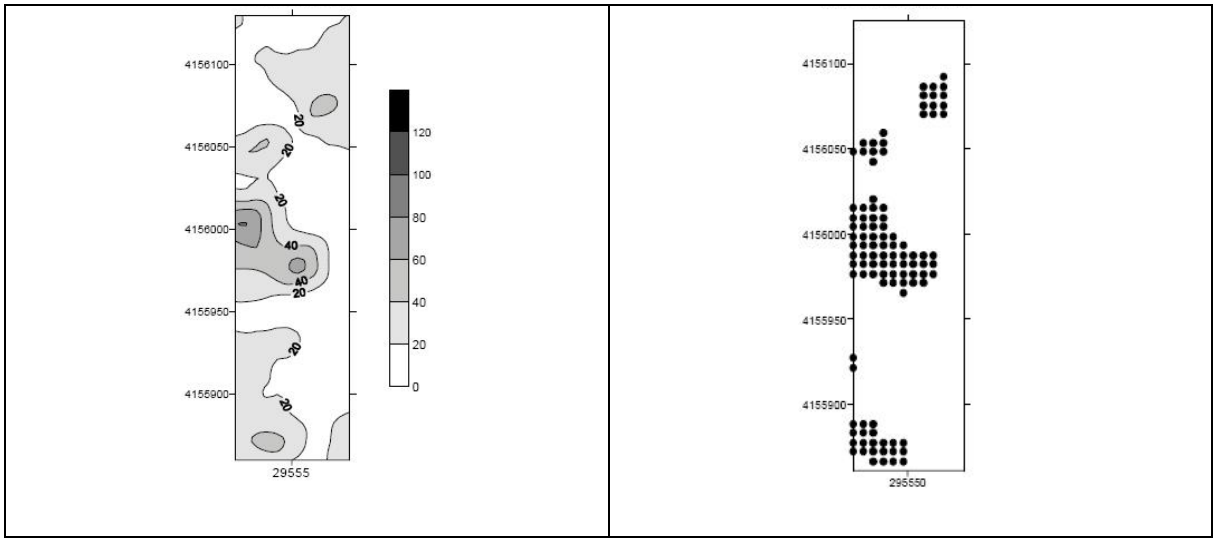

Figure 6.7: Left image shows density maps for *C. arvensis* in sunflower (axes represent Universal Transverse Mercator units, m, with vertical axis as Northing and horizontal axis as Easting); right image shows prescription herbicide application map based economic threshold limits (from Exposito et al., 2004).

Earlier work from Schuster et al. (2007) showed weed maps developed based on an off-field algorithm. These researchers compared these maps to prescription spray maps developed using a commercial

grid program with a weed threshold limit for spraying of 40 plants/m^2. Results from the herbicide application maps are given in figure 6. 8 and show the excellent comparison between the two methods (see Figure 6.3). However, as shown and briefly discussed earlier, the automatic weed mapping method underestimates weeds in the field and would result in an under application of herbicide.

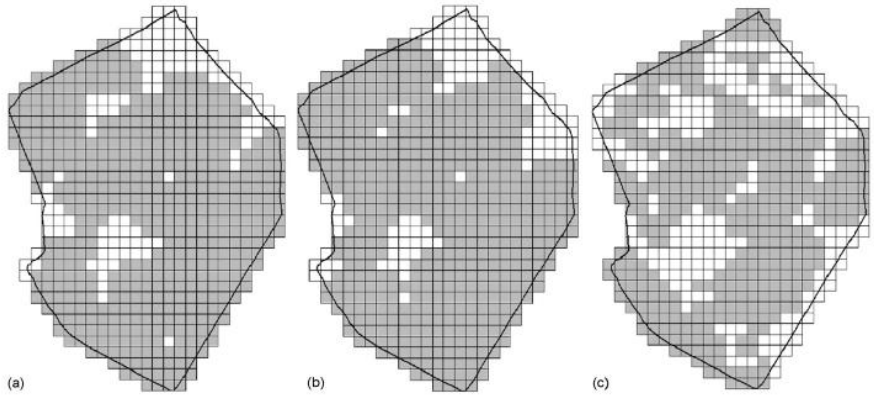

Figure 6.8: Spray application map for dicotyledonous weeds based a threshold of 40 plants/m^2 using (a) manual (b) semi-automatic and (c) automatic weed mapping methods (from Schuster, et al. 2007).

Present day applications using prescription application maps have dramatically changed since the early study reported above. For example, Bode and Bretthauer (2008) discuss geographic information systems (GIS) that are used for field information management reports including as applied chemical application maps, field prescription uploaded to the onboard tractor computer and controller systems for predetermined application rates, application reports annotating all conditions (including weather if instrumentation was available) of the spray application. Gerhards and Christensen (2006) discuss geostatistical methods that are used to quantify spatial dependence of weed seedling populations along with kriging methods to estimate weed maps at un-sampled positions (as previously shown in Garcia, 2006). Triangulation interpolation methods are also used to characterize weed seedling populations with a directional pattern. Interpolated weed maps have been reclassified based on weed infestation levels using geographic information systems and a weed treatment map created to provide a decision rule for spraying patches during spray applications is now common for spray applications.

6.3.3 Real-time control for chemical application

Stone et al. (2008) discussed automatic guidance systems for agricultural machines using differential GPS (DGPS) and real-time kinematic GPS (RTK) technology and the advancement of steering control systems for automatic steering. Stone et al. (2008) further predicted that the next step in these systems is development of fully autonomous, or robotic, agricultural equipment, however, there are few (if any) commercially available robotic field agricultural machines. Research on these systems has been active. However, in reality, the consensus is that safety, control and cost issues have impeded actual implementation of autonomous agricultural robots (Stone et al., 2008).

Bode and Bretthauer (2008) reasoned that sensor and controller development over the last several decades has been the primary driver for precision applications. Basically spray application now consists of controllers monitoring the application process and automatically adjusting spray application due to changes in speed, location and predetermined prescription for the application rate based on current needs in the field.

Moody et al. (2004) developed an automated data acquisition system (digital event recorder) for capturing field application data during operations. Twenty-four data channels were available for capturing information in addition to GPS locations during field operations. These researchers indicated that the system was used to catalogue information from a selective sprayer during in-field treatments. They compared results to map layers of foliage locations and sprayer actuation events. They also indicated the device could be used for late season herbicide applications for weed control and targeting locations for replanting after evaluating emergence from inaccurate seed plantings. The system used by Moody et al. (2004) was commercially available using sprayer heads with optical sensors that distinguish foliage from bare soil (Weedseeker™, Patchen Spraying Systems Inc., Ukiah, Calif.). Figure 6.9 shows how this system may be used on a small-scale field spray vehicle. The field application was in soybeans planted and allowed to grow for maximum canopy coverage (i.e., plants were allowed to grow four weeks for 100 % canopy coverage). Bare soil strips were secondarily tilled to remove secondary weed emergence. Additionally, data were required to be post-processed into a format for import into GIS. They concluded that the digital event recorder system was acceptable in documenting sprayer performance and accurately recording spatial information.

Figure 6.9: Weedseeker™ sensor interfaced to small scale spray boom for weed spraying in bare soil (from McCloskey, 2009).

Giles et al (2004) studied the effects of small, micro-liter applications to weeds within the seed-line of field grown tomatoes. Results indicated that dose rates of approximately 37 µL/cm^2 of a non-selective herbicide (glyphosate) deposited on weeds controlled weed growth during early growth when competition with the crop is critical. Additionally, this study successfully used a surfactant/polymer mixture to reduce inadvertent splash onto crop when weeds were in close proximity to the crop.

Downey et al. (2006) developed a direct injection system for at-nozzle injection. This is quite different than many direct injection systems that separate chemical and potable water. The system was able to inject chemicals at the nozzle with a 25 ms lag time (time of injection to 90% of concentration realized at nozzle exit). For pressures of 400 kPa, a 1% concentrate of injected solution with emitted spray was achieved within 100 ms.

Slaughter et al. (2008a) discussed a precision spray robotic system (figure 6.10) for weed control within the seed-line during early crop growth. The spraying system incorporated 8 independent spray ports with each port capable of spraying weeds in a 0.63 x 1.25 cm grid. A machine vision system discriminated weed from crop for targeted spray applications. The sprayer could treat up to a 10 cm wide transect across the seed-line in 10 ms. Later field tests showed good results with only 11 % of the weeds unsprayed and 21 % of the cotton plants sprayed. The advantage of this system is that non-selective herbicides can be used, however, concerns regarding inadvertent deposition on crop plants can result in significantly decreased yields. This is a continuing concern with small scale non-selective herbicide applications since the fundamental premise of the machine vision precision spray system is to control weeds within seed-lines adjacent to young crop plants (Slaughter et al. 2008b).

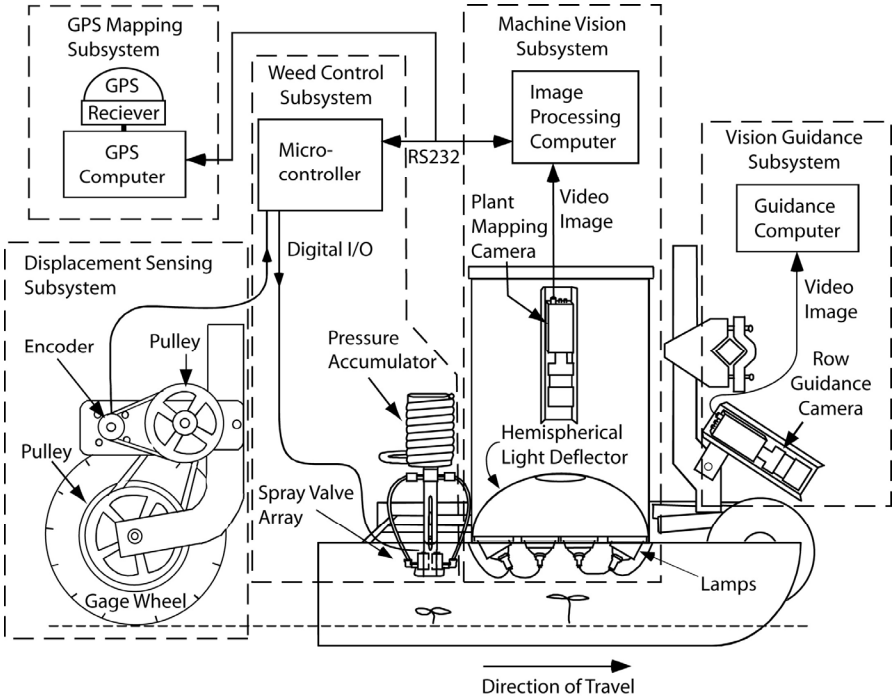

Figure 6.10: Rendition drawing for autonomous real-time weed control system (from Slaughter et al., 2008a).

6.3.4 Miscellaneous application systems

In a recent review on biological control applications, Giles et al. (2008) gave an introductory discussion regarding biological control methods including distribution of live insects, pheromones and predacious mites that require unique and novel mechanical handling systems. For example, Giles and Wunderlich (1998) developed a mechanical agitation suspension system for releasing beneficial insect eggs as biological control agents in vineyards. The system was able to deliver controlled volumes containing large droplets of suspension with contained larvae eggs and delivered suspensions for 50 min periods with no degradation of viability of beneficial insect eggs.

Wilson et al. (2004) reported on spray applications that reduced off-target spray deposition in citrus. Non-target deposition on water surfaces within an adjacent drainage canal in addition to surrounding ground surfaces was measured. The different spray scenarios included effects from turning the spray vehicle at row ends, leaving both banks of nozzles on, turning the outside-facing nozzles off or turning all nozzles off at the end of the foliage of the last tree within the row. Surface water deposition within adjacent drainage canals was reduced significantly when nozzles were turned off at the last tree within a row, or when the outside-facing nozzles-only were turned off through the end of row turns.

Another study (Giles and Downey, 2005) on target sensed spraying using ultrasonic sensors that turn on or off based on sensed tree locations established differences in spray partition depositions (tree deposit, ground deposit, drip from tree). Ground samples recovered were generally 50 - 75 % greater than recovered tree samples. A later study on orchard deposition assessments found that off-site drift movement ranged from 6 - 12 % depending on application rates during dormant applications and in season applications found off-target drift was 1 % of the spray application (Klassen et al., 2006). Additionally 187, 935 and 1870 L/ha application L/ha application rates were used for this study with the lowest application rate providing the best environmental protection for off-site movement, however, it is unknown what level of pest protection the lowest rates provide.

Solanelles (2006) discussed a prototype of an electronic control system based on ultrasonic sensors and proportional solenoid valves for proportional spray applications to tree crops. Liquid savings of 70%, 28% and 39% in comparison to a conventional application were recorded in the orchards studied.

Ferrell et al. (2002) evaluated manual applications of steam, flame weed treatments and selective herbicides for small plot growing conditions of strawberries, raspberries, vegetables, and orchard fruits. Their results found that steam treatment and the selective herbicide were ineffective and may have failed due to minor drought conditions. Manual flame treatment was the most effective weed control option of the three studied.

Sorensen and Jorgensen (2005) developed a band steaming weed control system for managing weeds in an organic farming operation that was technically, economically and commercially viable. Their results found that cost reductions were 72% when compared to manual weeding, however, they warned that profitability can be reduced if insufficient weed removal occurs compared with the efficient but hugely labor intensive manual weeding operations. Their study indicated cost reductions were about 80% when compared to manual weeding operations. Additionally, they concluded that expected developments within robotic methods for weed control coupled with navigation tools and weed recognition technology have great potential for treating in-line weeds in the future.

6.4 Remarks

Development of robotic weed control systems (on-the-go identification of weeds and application of herbicides) may reduce herbicide dependency and reduce environmental impacts from off-target depositions. Weed control is a significant issue; past analyses have documented yield losses due to inadequate weed control and uncontrolled weed competition (Slaughter, et al. 2008b). The most difficult weeds to remove are typically those done by hand hoeing; these weeds are the most competitive when competing with seed crops and can be most harmful to yield, especially if the crop was poorly seeded.

The dilemma with herbicide applications is that it is quite often efficacious and economically effective, however, continued public concern with chemical use and interest in organic products is limiting long-term acceptance for continued use (Slaughter et al., 2008b). Norremark et al. (2006) concluded that many of the application techniques developed over the years have a high degree of selectivity, that is, high selectivity for killing weeds while protecting crops. However, they have identified four concepts that should be further developed: laser or thermal treatments of stems or leaves, site specific in-line mowers, rotating steel rods and rotating vertical blades. Their study shows that there are alternatives to chemical control.

Automated, on-the-go, site-specific herbicide applications requires machine vision recognition for accurate plant/weed discrimination (including biological morphology, plant reflectance and visual texture) and in row removal mechanisms for eliminating weed competition. Responsible pesticide application requires protection of crops and distribution by efficient mechanical systems; protection of multiple non-targeted areas and humans is an ongoing requirement (Giles et al., 2008). Multiple new technologies have improved vehicle and resultant spray application equipment, spray nozzles and atomization devices and on-board sensing and control systems have been developed for these processes. New technologies has enabled an increase in spray application control that focuses on precise targeted placement for maximum effectiveness and efficiency while protecting non-target areas.

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7 Outlook and Remarks

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As discussed in section 3 of this chapter, there exists a large spatial and temporal variability in crop yield within a field even when it is managed uniformly. Although farmers knew that considerable variability in yield existed within fields, the extent of this variability was not fully realized until yield monitors became available to map crop yields. Yield variability may be associated with large spatial and temporal variability found in soil and plant characteristics as well as environmental factors. Wollenhaupt et al. (1997) discussed various sampling techniques that could be used to establish this variability. Basic survey/spatial sampling techniques and recent advances relevant for precision farming of specialty crops were reviewed in section 2 of this paper. Obtaining necessary soil and plant data on a site-specific basis is still an issue because of the lack of commercial yield monitors for the majority of the orchard crops and a lack of accurate and affordable sensors for key soil and plant characteristics such as soil mineral nitrogen, organic matter, phosphorous, etc. Lack of availability of such sensors makes acquisition of data tedious, time consuming, and expensive. Considerable work is currently underway to develop rapid and reliable soil and plant sensors to address these issues. Sections 4 and 6 discuss technology available to modify inputs in response to spatial variability in soil moisture and nutrient status, respectively. Section 5 deals with the issue of variability in soil nutrients and potential decision rules such as boundary line development system (BLDS) to apply site-specific amount of chemicals. As hinted in section 4, the lack of robust production functions is a major bottleneck in implementing site-specific irrigation. Bullock and Bullock (2000) have emphasized the need to develop yield meta-functions so that economically sound decisions can be made for variable rate nutrient management. Mano et al. (2003) pointed out that economically optimum N rates for corn may vary spatially due to spatial variability in soil characteristics and temporally due to environmental conditions. Bullock et al. (2003) have cautioned that failure to use site-specific input recommendations can lead to misallocations of resources just as great as due to using of regional averages (i.e., state-wide or regional input recommendations). They urged the need to develop site-specific nutrient recommendations. Most of the yield studies to date have tended to be on small plots and generally of one to two year duration (Bullock and Lowenberg-Deboer, 2007). Longer term, multi-region agronomic experiments are essential to develop spatially variable nutrient rate prescriptions. Bullock et al. (2009) pointed out that except for light-bar technology and GPS based autoguidance systems, adoption of precision technologies has been limited. Bullock et al. (2002) remarked that the principal cause of non-profitability or low adoption rate of variable nutrient application technology is insufficient information on crop yield as a function of managed inputs, field characteristics, and weather. The use of *ex post* rather than *ex ante* decision making has led to often confusing and contradictory results (Bullock et al., 2009). They claimed that crop yield can be represented in terms of nature's yield meta-function of the form:

$$y = f(x, c, z) \tag{7.1}$$

where, *y* is crop yield, *x* is a vector of managed inputs such as fertilizers, *c* is a vector of soil characteristics such as textures, and z is stochastic variable such as weather. They urged for long term, multi-region experiments to determine nature's yield meta-function supported by public funds for public good. A site-specific yield function will result if a specific field with fixed characteristics, *c*, is considered. In such cases, the yield function becomes:

$$y = g(x, z) \quad (7.2)$$

Precision technologies such as variable rate nutrient and irrigation management can be used to obtain data necessary to establish the nature of equation (7.1) and (7.2) using large plots with their inherent variability. Thus precision technologies can be important research tools that can be used to develop nature's meta- or site-specific yield functions that can become the basis for economically sound decision support system. Concerted effort on the development of sensors for soil and plant characteristics including yield monitors for specialty crops, and nature's yield meta-functions through multi-year and multi-region research are necessary to establish scientifically and economically sound decision support system to implement variable input management guidelines using precision technologies. Various research activities currently underway in addressing the above two issues will play a pivotal role in guiding information based site-specific and/or plant-specific agriculture in general, and specialty crop production in particular.

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