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# Zoning and Data Fusion in Precision Horticulture: Current and Needed Capabilities to Assist Decision-Making

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## **Abstract**

Management zoning has been one of the main ways that spatial agricultural data sets have been used in precision agriculture, particular as a means of data-fusion between multiple information layers. As with most precision agriculture technologies and methodologies, management zones began with arable cropping systems but have been adopted into perennial cropping systems. This review brief explores the evolution of management zones in agriculture (with an emphasis on horticulture), the basic concept, the key research areas in management zone delineation to date and the diverse ways that management zones have been applied into arable and perennial systems to support crop management. The future role of management zones, including their relevance in cropping systems with higher resolution information sources is discussed, along with the future need to have more spatio-temporally dynamic zones to respond to decision-specific management and to accommodate increasing availabilities of in-season information. To support this, a new concept of decision zones is proposed that is decision driven, more flexible in its data-fusion processing and simplifies the final zoning process. Management zones are expected to continue to be an important first step in understanding spatial relationships when entering into precision horticulture. They will also be important for site-specific crop management in the early stages of adoption when data layers are likely to be limited. However, as data and information layers accrue for a cropping system, and spatial understanding of production drivers and interactions develops, then 'decision zoning' should replace the current idea of management zones.

## **Keywords:**

Management zones, precision agriculture, *k*-means clustering, segmentation, decision support systems, Decision zones.

## **INTRODUCTION**

Site-specific crop management, which includes horticultural crops, is contingent on being able to move from 'average' decisions at the field-scale to subfield-scale decisions and operations. This potential change is dependent on the scale at which data/information is available and on the ability of farm machinery to implement the decisions. Figure 1 shows that this is an evolution. As sensing, decision-making and operational capabilities improve, the industry will shift ever closer to real site-specific (i.e. plant or even leaf-specific) management. In the interim, however, it is widely recognised that some intermediate resolution of management is needed. This is generally referred to as the management zone or management class concept. Lark and Stafford (1997) originally proposed the term 'management units'; however, the term 'management zones' is more commonly used in Precision Agriculture (PA) to describe delineating a field into smaller subfield areas for differential management operations. This can be somewhat ambiguous as the majority of statistical methods used are based on classification algorithms that produce 'management classes'. The difference is important (Pedroso et al. 2010). A *management zone* (MZ) is a spatially contiguous (discrete) subfield area to which a particular treatment may be applied. A *management class* (MC) is the entire subfield area over which a particular treatment may be applied. This may constitute more than one zone. A *management unit* (MU) for the purpose of this article is a generic term that encompasses the idea of both MCs and MZs.

Management units play a key role in getting producers involved in PA. When done correctly, the producers can see how the various, often complex production layers are compressed into a single,

usable map that can be interpreted with their existing local knowledge of crop and soil responses. Individual MUs can be treated as virtual, fenceless fields. Decisions follow a field-scale process, i.e. the general agronomy process of the grower/agronomist remains unchanged, but is applied at a smaller scale (i.e. the MU instead of field scale). This achieves a higher level of spatial management while maintaining the producer in a familiar decision space. Of course, if poorly constructed, MUs will be uninterpretable, the producer will be disillusioned with PA and the default uniform field management will continue to be used. As a result, a large part of PA research has been directed at issues around generating correct MUs. However, the majority of this research has been predicated on some level of expert or grower intervention in the MU delineation approach. While the majority of the work to date has focussed on arable cropping systems (Corwin and Lesch, 2010; Clay et al., 2017), tools developed for MU delineation are as relevant to perennial horticultural systems (e.g. Manfrini et al., 2020; Zude-Sasse et al., 2016) as they are to arable cropping systems.

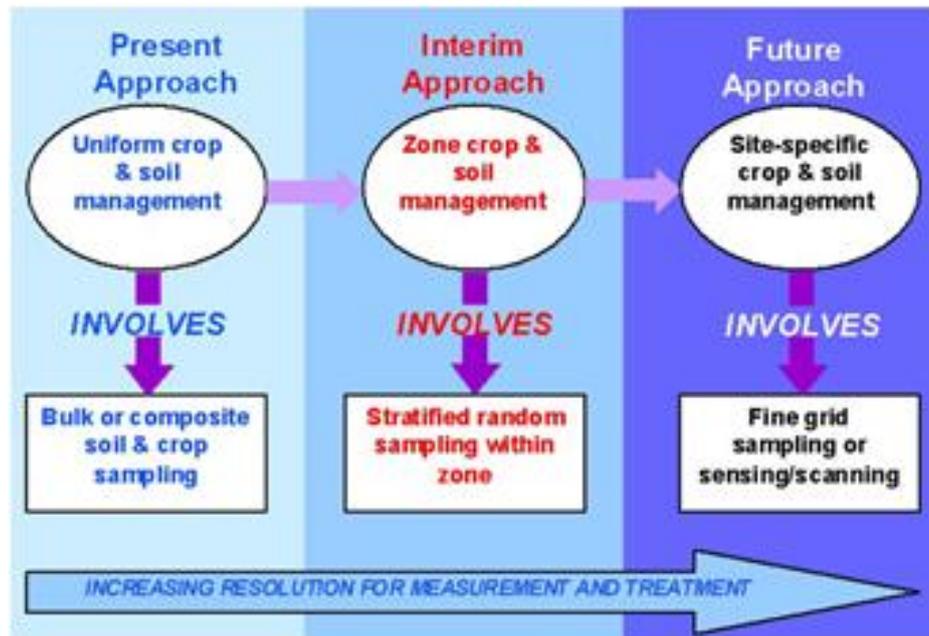


Figure 1: Schematic illustrating the shift from a conventional uniform field management strategy to a true site by site-specific management strategy by using zone (management unit) management as an intermediate. The required increase in data with the shifts are also indicated. (Image courtesy of the Precision Agriculture Laboratory, The University of Sydney).

### **DELINEATING MANAGEMENT UNITS FOR PRECISION AGRICULTURE/HORTICULTURE**

Management units were advocated very early on in the application of PA as a means of interpreting observed crop and soil variation (Lark and Stafford, 1997). The delineation of MUs tends to use some form of expert knowledge system or multivariate analysis to identify areas of a field where crop and soil responses are similar to make these virtual, fenceless subfields within a field. These 'subfields' or MUs are then managed as a single entity. However, each MU in a field has a different production potential (or different production-limiting factor) that can be managed differentially to greater effect. While developed within arable fields (Fridgen et al., 2004; Corwin and Lesch, 2010), the concept of MUs has been successfully applied to many other systems, including perennial horticultural and viticulture systems (e.g. Farooque et al., 2012; Bramley and Lamb, 2003).

How MUs are derived and how effectively they partition the within-field crop and soil variation will ultimately determine how useful they are for PA. There will always be some trade-off between the number of MUs, the production differences between MUs and the size and shape of each individual unit. Too few MUs and the variance in production is not adequately described. Too many MUs will generate small and irregularly shaped units, which are operationally difficult to manage, and small production differences between MUs that may or may not be real or manageable. To address these issues, there has been a considerable research effort on MUs within the PA community over the past 20 years.

## Key Research Areas to date

Since MU delineation is dependent on the input data, the quality (uncertainty) in the data/information used for zoning will have a potentially large impact on the MU derived, regardless of the method of delineation used. It was evident from conference presentations in the late 1990s and early 2000s that many researchers were incorrectly generating MUs, either through poor choices in data pre-processing (filtering), interpolation or multi-variate data-fusion. Protocols and methodologies to properly clean, filter and interpolate all sorts of agricultural data have been widely published (Sun et al., 2013; OTHERS??) and should be used to ensure that the best quality information is fed into the zoning algorithm. Many of the spatial data cleaning algorithms are equally applicable to horticultural data as to arable cropping data.

### *Delineation Methods:*

In their simplest form, MUs are based on a single layer, usually a soil map, that is divided into areas of different response. The univariate system is fairly simple for 'zoning' using typical cartographical divisors e.g. Jenks, equal interval etc. However, in the majority of cases, MUs integrate multiple data and information layers to simplify these disparate spatial data sets into a single, more interpretable map. The most common method for this data fusion has been by using variants of  $k$ -means clustering (e.g. Lark and Stafford, 1997, Fridgen et al., 2004; Frogbrook and Oliver 2007; Castrignano et al., 2009, Arnó et al., 2011; Cordoba et al., 2016 among others). However, it does have limitations. It requires data to be co-located, which in turn requires correct interpolation as a pre-processing step as data collected on different days and/or with different sensors are unlikely to be co-located. Interpolation is usually needed for mapping and correct visual interpretation of the data. However, it is not directly necessary for MU derivation and, ideally, it would be preferable not to have to do this. The  $k$ -means algorithm clusters data in the attribute space and the result is projected onto a map. This generates classes, not discrete zones. The data are considered to be independent and are not usually spatially constrained so it is normal to have small unmanageable 'zones' generated in the final map. The general process is outlined in Figure 2 (from Taylor et al., 2007). Various approaches have been proposed to address some of these limitations, including incorporating a spatial constraint within the  $k$ -means algorithm (Frogbrook and Oliver 2007), filtering the derived zones with either spatial (e.g. Ping and Doberman, 2003) or statistical filters (Cordoba et al., 2016, Sun et al., 2013) or forcing classification into regular shapes (e.g. Cid-Garcia et al., 2013).

Several segmentation algorithms have also been proposed to generate spatially contiguous zones (e.g. Roudier et al. 2008, Pedroso et al., 2010, De Benedetto et al., 2013; Leroux et al., 2018) to avoid fragmented zoning, although irregular shaped zones remain problematic. Segmentation is an alternative method of data fusion, usually applied to images using either a region-based or contour-based algorithm. Region-based are more common and operate via region-merging or region-splitting approaches. A region is considered a point/pixel (or set of points/pixels) and is merged (or split) with (or into) neighbours based on neighbourhood statistics. It has been demonstrated to be an effective method for zoning (Pedroso et al., 2010) but rarely applied compared to the  $k$ -means approaches.

### *Selection of the optimal number of zones/classes – choice of a stopping criterion:*

Regardless of the choice of zoning algorithm used, selecting the right number of classes/zones/units is a key decision, and probably the most subjective decision in making MU maps. For the  $k$ -means classification approach, a value of  $k < 5$  is usually optimum (Whelan and McBratney 2003; Fridgen et al., 2004; Pedroso et al., 2010) when quantifying the amount of variance in production explained by the classes against some subjective appraisal of the number and size of the discrete individual zones generated by the classification. (It is important to note that there will be many more discrete zones than there are classes.) For segmentation approaches, there is little scientific support for deciding the optimum number of zones, and it is very much an expert-driven process at the moment although the use of non-parametric significance tests have been proposed (De Benedetto et al., 2013). So, from a delineation perspective, the question of which method and what level of MUs is best for management, is still an open one. Direct comparisons between methods and numbers of MUs are rare in the literature. One early approach by Pedroso et al. (2010) clearly demonstrated the difference in MU output between classification and segmentation (Fig. 3). Classification and segmentation are very different algorithms, and the difference between a 2, 4, 6 and 10 unit solution is clear in Figure 3. For example, the 4-class solution in Figure 3 has 30 zones of a

manageable size (Pedroso et al., 2010), therefore the  $k = 4$  solution should be referenced against the 30-zone solution. However, while some indicative analysis based on variance partition is proposed by Pedroso et al (2010), an optimisation function for comparing levels of MUs, especially across methods, is not given. Such an optimisation function needs to consider the size and shape of MUs, the difference in production levels between units, the machinery available and a producer's intent as well as effectiveness of the MU output in describing the observed production variation (yield, biomass, soil properties, etc...).

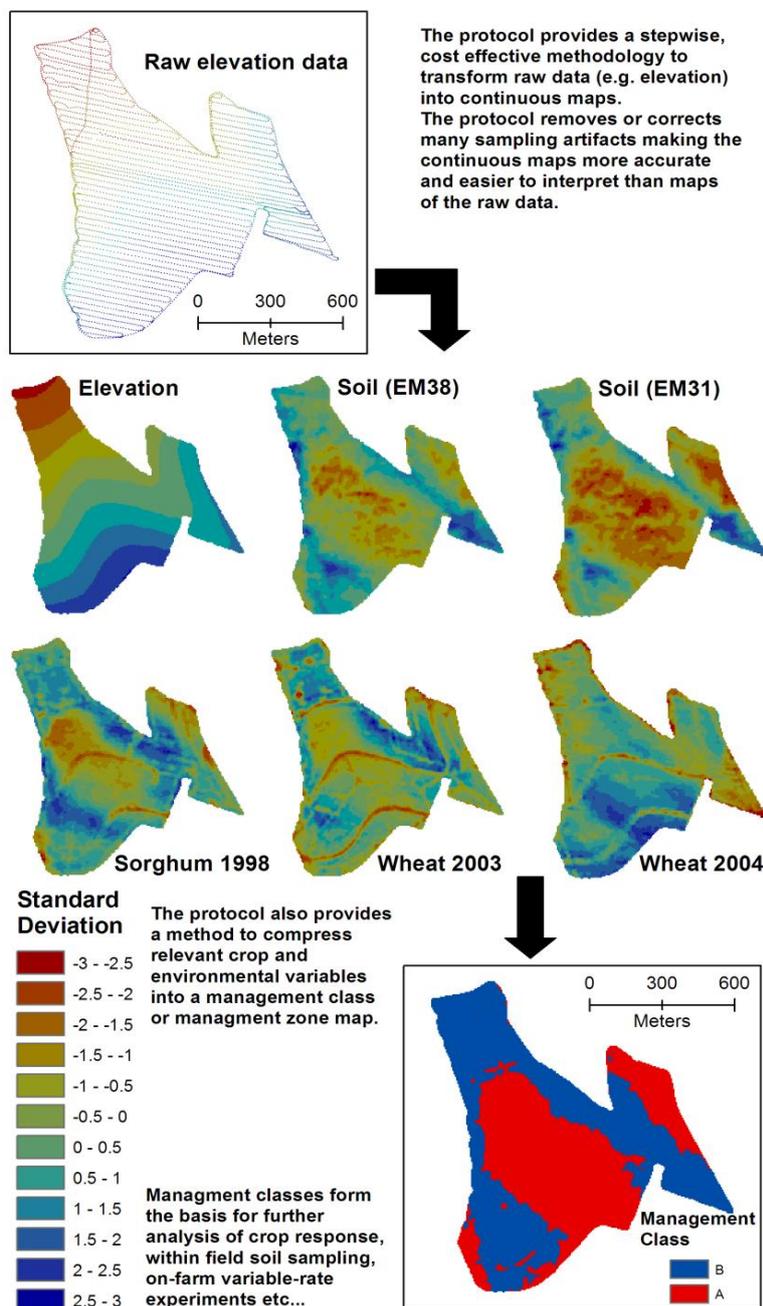


Figure 2: A visual illustration of the protocol outlined in Taylor et al. (2007) to transform raw irregular crop and environmental data into flat single layer maps and the fusion of these layers into a potential 2-management unit map (using  $k$ -means classification). The image was first published in CSA News, which is an industry magazine that supports research published within ASA, CSSA and SSSA journals.

A determination of the difference in response between MUs is usually done statistically, often by means comparison, e.g. the mean yield of each MU (Fridgen et al., 2004; Taylor et al., 2007; Manfrini et al., 2009). However, a statistical difference does not necessarily equate to an agronomic difference (and vice versa). A difference of 1 t.ha<sup>-1</sup> in yield would be interpreted differently by grain growers in

semi-arid regions vs. cool-climate regions and likewise would be interpreted very differently between perennial horticultural systems and arable cereal systems. An alternative to direct means comparison is to use statistics associated with the partitioning process. It is for this reason that the fuzzy variant of  $k$ -means clustering is often advocated (Boydell and McBratney, 2002; Gavioli et al., 2016). It generates partitioning and entropy indices, based on likely memberships, which can be used to identify the most 'stable' solution. This, however, is also a purely statistical metric, although based on a standardisation of the production attributes. Again, there is no direct consideration of the agronomic difference and if it is worth managing differentially. Metrics to help growers should incorporate an understanding of the level of difference between MUs that a grower would act on (as well as the variability within MUs). Ultimately, this is a factor that is grower-specific, based on their level of risk management (which inherent captures their level of economic security) as well as their production objectives (target markets). Taylor et al. (2007) proposed an alternative confidence interval based on the median error of prediction in the maps that were used for the MU delineation. This supplied growers with information on the difference in means and a likely error and provided the opportunity for them to make their own assessment of the significance of agronomic differences between MUs. More recently, Loisel et al. (2019) have provided a numerical criterion to rank a set of possible outcomes from a delineation process (different numbers of classes and zones).

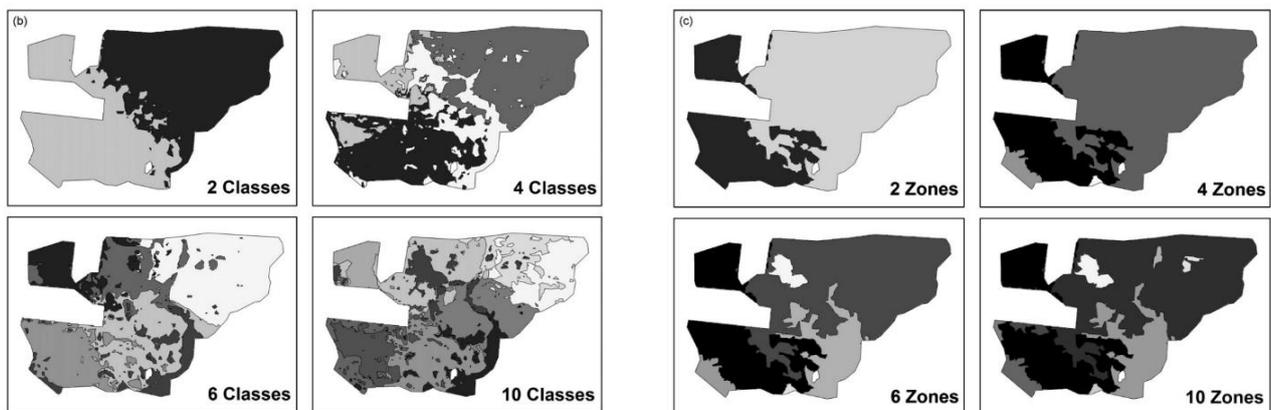


Figure 3: A comparison of the application of a spatially constrained classification (left - 'Classes') (using the method of Frogbrook and Oliver, 2007) and a segmentation (right - 'Zones') algorithm (Pedroso et al., 2010) to the same canopy vigour data in a vineyard in Spain. For both approaches a 2, 4, 6 and 10 'class' solution is presented. For classification, this generates  $k$  classes, while the segmentation generates  $k$  (discrete) zones. The 4-class solution explains a similar level of variance as the 10-zone map but has three times as many discrete manageable 'zones' (after excluding the many small, unmanageable zones generated). (Image and details reproduced from Pedroso et al., 2010).

#### *Selection and weighting of input layers for MU delineation:*

Selecting the right layers to use in the process is also important to the outcome, but less researched. In general, the selection of input layers is at the discretion of the user, i.e. it is an expert choice. Historically, this has not been a major problem as the number of data layers has been small. However, every year the number of available layers is increasing, making correct selection more difficult, or alternatively stated, increasing the likelihood of including redundant or erroneous data. As for any modelling system, the 'garbage in, garbage out' paradigm is relevant here, so selection of the wrong layers generates a wrong outcome.

With more data generated, and more fields being connected and analysed, data-mining techniques to select preferred layers will become more necessary. Maps/layers with strange effects should not be used for MU delineation (unless the strange effect is permanent and intended to be managed), so tools to identify if a map is 'strange' are needed for automated processes. In this light, the use of principal components analysis (PCA) has been proven to be effective (Georgi et al., 2018; Blasch et al., 2020). However, other data-mining approaches are also likely to be applicable. Alternative data-mining approaches may also be suitable for selecting preferred layers across heterogeneous sets, e.g. simultaneously selecting preferred yield, canopy and soil data layers for the MU process, but is an area

poorly developed to date. An alternative approach to assist in selecting the right ancillary data is to use MANOVA with an information criterion (Taylor and Whelan, 2011; Uribeetxebarria et al., 2018). This is perhaps the sole area where research in Precision Horticulture (PH) is in advance of arable PA systems. This is likely an artefact of the slower development of PH and the availability of more data layers at the start of the process, and hence the need for methods to select the optimum or preferred data layers.

### Summary of the traditional model for management unit delineation

Regardless of the method used for selecting input data, delineating units and determining the final number of MUs, research in this area in all aspects of crop production has followed the same model (Fig. 4), where data is collected, zoned into MUs and then agronomic decisions are applied to these zones. Typically, all agronomic decisions are applied to the same MU map, from seeding, to fertiliser, to crop protection decisions. As indicated previously, expert knowledge is required to select input data layers and in determining the number of MUs. However, the dominant area where agronomic knowledge is used in the process is in the final stage of adapting the output MU map to each differing decision.

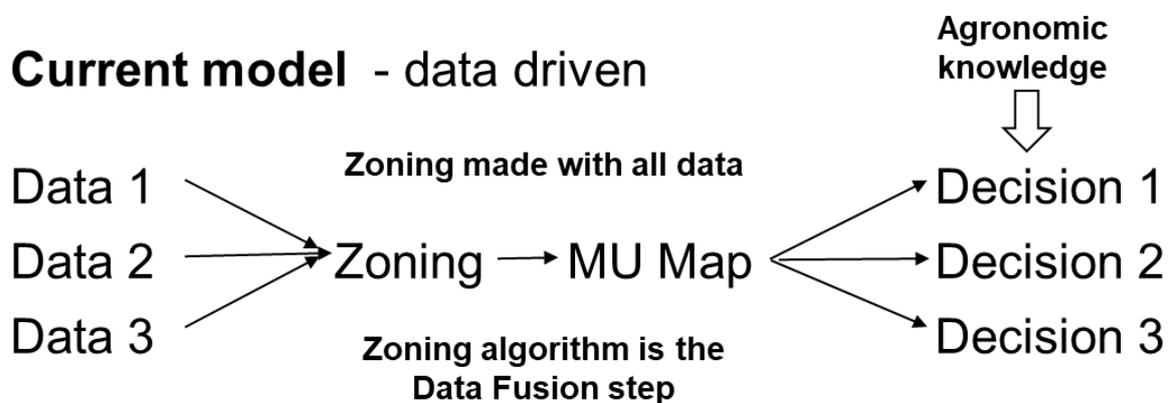


Figure 4: Schematic illustrating the basic process used for delineating management zones since the inception of Precision Agriculture. It typically uses all available data (of suitable quality) in a zoning algorithm that acts as a data-fusion engine to generate a single output (management unit map) to which decisions for multiple agronomic operations are applied.

The process outlined in Fig. 4 for delineating MUs and applying them to production systems has been very useful for translating normal agronomic decisions into a subfield region. This does not fundamentally change the agronomy. The MUs are used to set different yield potentials in different parts of the field. Decisions are being made at a higher spatial resolution, but the fundamental decision process is not changed. The same management style is used across all MUs, just tailored to a different (MU-specific) yield potential. Generic, regional response functions are nearly always used to drive decisions, even though it is unlikely that any particular field or any particular MU has that exact response function. This process is equally true for perennial horticultural systems as it is for arable cropping systems (where it has been predominantly deployed to date).

### ALTERNATIVE APPLICATIONS OF MANAGEMENT UNITS IN AGRICULTURE

As well assisting with improved agronomic management, MUs can also be used in other contexts. These include:

- Forming a base for improved sampling in agricultural systems (Martinez-Casasnovas et al., 2012; Urretavizcaya et al., 2014; Herrero Langreo et al., 2017; Manfrini et al., 2015 and 2020). The MUs can be used for various stratified sampling schemes that have been shown to improve the efficacy of sampling in crop systems, including horticultural systems. This is particularly important for perennial cropping systems that require effective sampling methods for accurate estimations of fruit load (yield) (e.g. Miranda et al., 2018; Uribeetxebarria et al., 2019).

- As a basis for spatial crop modelling. Just as MUs are a way of changing the spatial resolution of management, they can also be the basis for changing the scale at which crop models are applied into a production system (Basso et al., 2011; Zha et al., 2019) OTHERS??). By definition, MUs tend to be more homogenous in production, and this uniformity in environmental/production conditions enables models to be applied at higher spatial resolutions than they normally are. It is a logical first step towards using crop models in a tactical way for management in precision agriculture.
- Designing on-farm experiments (OFE). To be effective, experiments should account for variance in the system. This is not easy in open biological systems, like agricultural fields. Generating MUs is effectively a method for partitioning variance in the production and environmental data sets and has been shown to be an effective way of restructuring on-farm trials (Whelan et al., 2012). This is a new method of experimentation and still needs the development of methods for statistical and agronomical interpretation of these data to gain acceptance (Marchant et al., 2018).
- Interrogating Spatial relationships. The generation of MUs typically requires detailed yield, soil and/or biomass maps. The simplified trends within the derived MUs form a starting point to investigate spatial patterns in the data. This helps to better understand spatial variability in crop productivity (e.g. Manfrini et al., 2020; Aggelopoulou et al., 2013) and improves local knowledge of spatial crop responses before any further analysis is performed (crop modelling, OFE, etc...). This is an important step in engaging new entrants to precision agriculture with spatial agronomy.

### **IS ZONING STILL RELEVANT?**

With increasing levels of high-resolution data becoming available and more being proposed, there is a general trend towards being able to measure and model at scales that approximate the individual plant-scale. This is particularly true in perennial, large tree crops, where an individual tree has a relatively large spatial footprint. Plant (tree or vine) specific management should be the ultimate goal. Under this scenario, the value and viability of MUs going forward may be questionable. Plant-specific management will require all available data/information to be either measured or modelled at the scale of an individual plant or to be downscaled to the plant-scale. It also assumes that neighbouring and stochastic effects can be correctly accounted for in any measurement or model. Similarly, making a decision at a plant-scale implies that management (field operations) can be applied at the individual plant-scale.

However, in the short to medium-term, it is hard to see true 'plant-specific' management being adopted. Measuring, modelling or downscaling to a plant level is unattainable for most data/information sources. From a management perspective, some field (plant) operations can be targeted to individual plants (e.g. pruning) (Murray et al., 2019; Filippo et al., 2020), but other operations, e.g. variable rate irrigation, are still currently difficult or impossible at the plant level. There is also an economic perspective to management at this super-fine resolution that is not well understood at the moment. Scaled cost-benefit analyses are still missing in the precision horticulture literature. However, it is likely that perennial horticultural systems will be the first to arrive at the possibility of having true plant-specific. In the meantime, MUs remain a valuable tool for integrating data, making informed decisions and developing differential management strategies. They are a means of effectively smoothing some of the uncertainty and of developing spatial decisions that are tailored to reflect the scale of the data/information available and of the decisions to be implemented. As data/information improves, modelling advances and technology develops, the average size of individual MUs will undoubtedly decrease and eventually approximate a plant-specific response (1 MU = 1 plant).

### **EVOLVING DYNAMIC MANAGEMENT UNIT DELINEATION – CONCEPT OF DECISION ZONES**

The delineation of management units (MUs) using classification methods was a big step forward in multi-layer data fusion (Lark and Stafford, 1997, Fridgen et al., 2004). However, the current use of MUs tends towards static patterns and they are applied as a 'one size fits all' approach (see Fig. 4). Fixed zones, with fixed boundaries, are used for all potential variable rate applications – for example planting, chemical inputs and fertiliser. This is (was) sensible with only limited numbers of information layers available. With more information, particularly in-season temporal information,

becoming available for both crop and soil properties, there is a new opportunity to tailor management units to specific operations and times in the season, i.e. MUs should be dynamic in space and time (Scuderio et al., 2018; Clay et al., 2017). For example, the drivers of variable plant establishment will likely differ from the drivers of variable crop development in any given field. In such cases, MUs for variable-rate seeding and variable-rate fertiliser should differ. However, it is only recently that data and information availability, linked with improved connectivity, has reached a level where the potential of using dynamic MUs is a reality (Scuderio et al., 2018).

The potential for dynamic MUs, generates a new paradigm for essentially the same set of questions and challenges. How is the right data chosen in an automated way for these dynamic MUs? Which method of data fusion should be used to generate MUs that evolve with decisions and/or time? Currently, with fixed, static MUs, the delineation is performed by an expert in consultation with the producer. This ensures a rigorous selection of input data and a standardised method of delineation. A shift to dynamic MUs will make this approach economically unsustainable. Service suppliers will not be able to provide the level of personal contact needed to be constantly altering MUs with evolving seasonal conditions and for disparate management operations. It will be the producer and/or an automated system, built on artificial intelligence and machine-learning approaches that will likely generate these dynamic MUs in the future. The current (and future) expert knowledge, of both the agronomist and producer, in selecting the relevant data for specific operations, and the method of MU delineation needs to be captured within an autonomous (self-learning) model to allow producers to derive MUs with confidence by themselves.

This is not an easy objective. This shifts MU delineation from an *information intensive* system to an *embedded knowledge* system (Miller et al., 2019). More robust and repeatable data fusion methods are needed to replace the current use of *k*-means classification (and its derivatives). Ideally, as proposed in Leroux et al. (2018), these multivariate data fusion techniques should operate directly on the raw data and include filtering and pre-processing steps. Machine-learning techniques, particularly techniques that enable soft-computing solutions, are likely to be at the forefront of this approach to MU delineation.

## **A NEW CONCEPTUAL DECISION-DRIVEN APPROACH TO MANAGEMENT UNIT DELINEATION**

If the current model for (static) MU delineation is considered as a data-driven model (Fig. 4), then the shift to dynamic MUs will require the adoption of a decision-driven model for MU delineation, i.e. each management decision to be made should potentially generate its own MUs that are tailored for that decision. This process must start with the decision, rather than have it imposed at the end of the process. Similarly, agronomic knowledge related to the decision to be made needs to be incorporated earlier in the delineation process. All available data/information should be available for any decision, but it is the decision, the grower's knowledge and preferably the grower's production goals and risk strategy that determines which data/information is relevant to the decision.

As illustrated in Figure 5 (and in comparison with Fig. 4), this concept is a fundamental change in where the data fusion occurs and how zoning algorithms are used. The removal of the data-fusion step from the zoning process will open up a large area of needed research into how to select and fuse data/information layers within a decision process (instead of a zoning process). To succeed this will necessitate a shift towards machine-learning, artificial intelligence and other soft-computing approaches, both in the choice of layers and the formalisation of the decision (Chlingaryan et al., 2018, Liakos et al. 2018). The latter is particularly important as all growers will have different production targets, different economic constraints and different risk management profiles. In simpler terms, presenting the same data to two different growers will also certainly generate a different (albeit possibly similar) MU map based on each grower's knowledge, risk and production goals.

Once a (spatial) decision has been made, a choice is then needed on which method of zoning algorithm is optimal for delineating the decision-specific MUs. Note that in this process the zoning is not part of the data-fusion process and is applied to a univariate output. There is a fundamental shift in the use of a zoning algorithm from a method of data fusion/compression to a method for technical management of fields. Zoning becomes a way of translating the decision output layer into a form that can be differentially applied within a production system. The management units that are generated from this process are effectively **decision zones**. It should be noted that term "decision zone" has been deliberately used in preference to "decision unit". This is intended, as the sole intent is to generate larger, stable spatial zones for operational reasons.

This of course generates questions as to where the scientific and research questions lie to make this new concept operational, and do these questions differ from the historical areas of research into MUs? The removal of the data fusion process from the zoning algorithm makes the generation of zones (or MUs) much simpler. It becomes an objective function based on the minimum size of zone that it is possible to manage, the minimum treatment difference between zones that can be applied by available technology and the economic cost function of variable-rate management. Several existing methods for zoning univariate data are applicable to deliver coherently shaped (spatially constrained) DZs (Tisseyre and McBratney, 2008) that have been correctly assessed to remove unmanageable zones (Betzek et al., 2018). Consequently, there will be some limited research interest in the use of alternative algorithms for pattern recognition in DZ delineation. However, the influence of the potential choice algorithm used will ultimately be less important to the outcome than in the traditional approach (Fig. 4).

Within a dynamic system, there is no restriction on the use of an existing decision zone (DZ) as an available data layer for a future decision (and DZ map). For instance, a DZ map generated for variable-rate pruning could be used as information to help decide on DZs for a future variable-rate spray application.

### Proposed model - decision driven

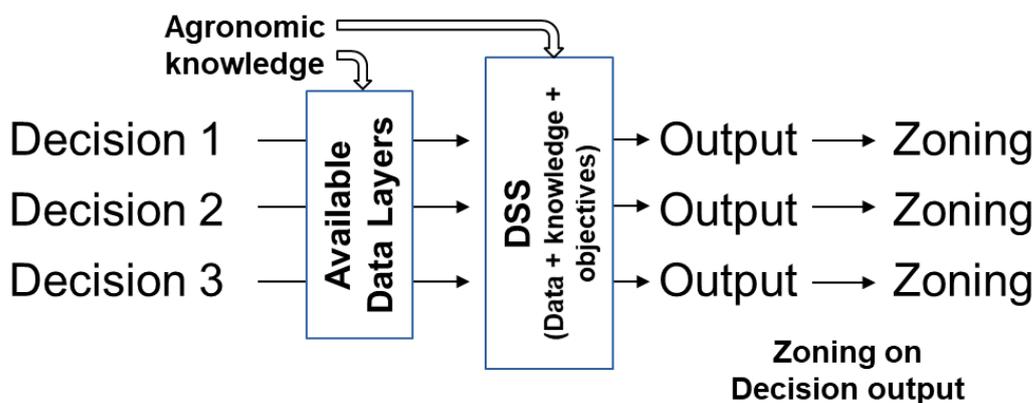


Figure 5: A schematic illustrating a proposed decision driven model for deriving decision (management) zones. Agronomic knowledge is capture in the selection of input layers and within a decision support system and zoning is only performed on spatial decision outputs (rather than on inputs – see Figure 4). The data selected for the decision and zoning (from all available data) will be driven by the type of decision being made.

An example of this from a recent paper is presented in Figure 6 (Guillaume et al., 2020). In this example, a fuzzy inference system has been designed by both a grower and an extension viticulturist to determine N fertiliser rates within a vineyard. The starting point is a decision, which is the same for both growers. Because this is applied to a common production system, the available information is also common for both growers. The three common data layers pertain to soil variability, vine size and productivity, which all help to inform the grower of how much nitrogen will be required by the vines. However, growers and extension agents have different perceptions on ideal vine size and productivity. The knowledge and information that they pass to the decision (data-fusion) process differs. Consequently, different N fertiliser zones are generated, even if the general trends of where to apply more and where to apply less are similar between the two (see Guillaume et al. 2020 for full details). In this case, neither DZ can be considered wrong. Each DZ is tuned to the knowledge and expected targets of each end-user (grower vs. extension agent).

The example presented in Figure 6 has used a fuzzy inference system to merge the user’s knowledge and objectives with the spatial vineyard layers. However, fuzzy approaches are just one of many possible approaches that can be used here, and many existing and emerging machine-learning approaches are potentially equally applicable. The key point with this change in data fusion is to ensure an ability for the grower to engage with the decision process and incorporate their knowledge and needs into it. Systems that are simpler and more transparent in achieving this are likely to be

more readily adopted (Li et al., 2020). Without engaging a grower (or end-user) at the start of the process, i.e. in the decision support component, they are unlikely to have faith in the resulting output. This is certainly an area where considerably more research is needed. Within this decision process (data fusion) there will also need to be some form of selection process to identify suitable data layers. This again can be performed via automated processes (e.g. Blasch et al., 2020) involving machine-learning algorithms that are tailored to specific crop systems (crop and/or region) and growers.

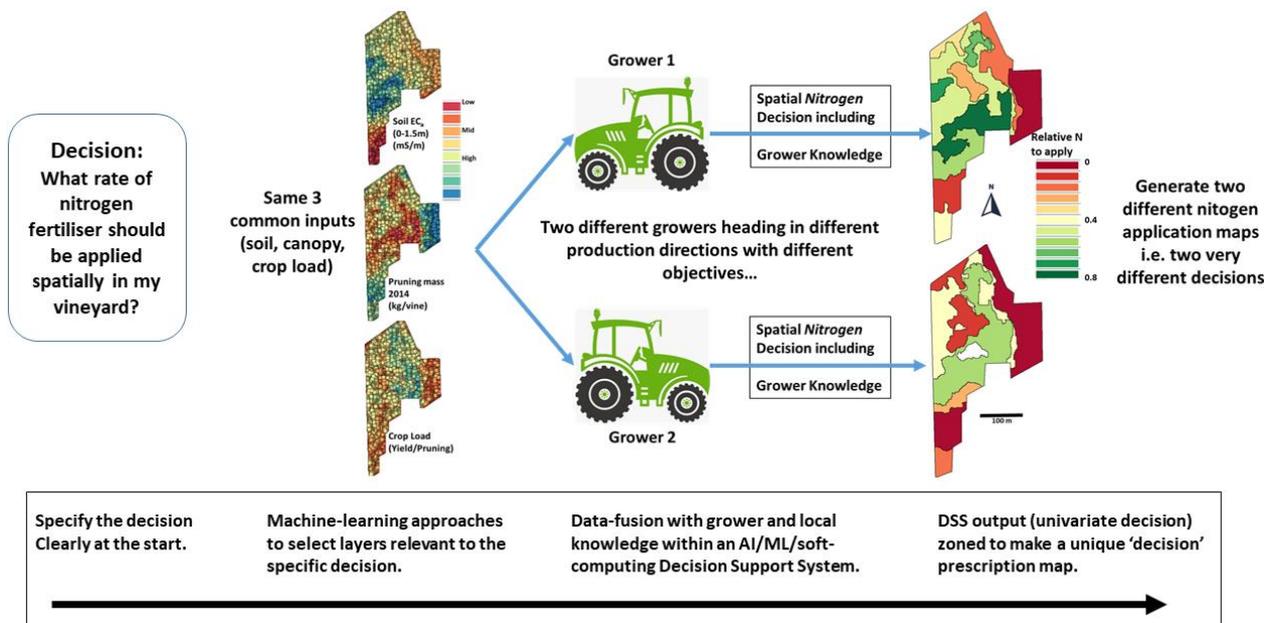


Figure 6: An illustrative schematic of how decision zoning operates by a) specifying the decision first, b) selecting data layers relevant to the decision (from all available layers), c) using a dedicated data-fusion tool that includes grower knowledge and d) zoning only the output (decision) from the decision support system. Adapted from Guillaume et al. (2020).

Perennial horticulture production systems are generally high value crops, and high-value crops tend to be more amenable to the capital or economic investment needed for precision horticulture. They are also good candidates for this shift from MUs to DZs as profitability is strongly linked to the quality of production and there is often a trade-off between the quality and quantity of production. Producers should be able to ensure a return on investment in precision horticulture by improving this trade-off to their benefit. This will all come down to making effective spatio-temporal decision zones and making the production system as dynamic and flexible as possible.

## CONCLUSION

Defining management units/zones has been an integral part of the development of precision agriculture, particularly in arable crops. Primarily this has been used as a data fusion step to aid subfield management. However, increases in data availability and advances in machine-learning approaches are changing the possibilities for data-fusion in agriculture. Given this changing landscape, management units are becoming obsolete for subfield management and a new concept of decision zones is proposed as a replacement. Decision zones are dynamic and specifically designed to spatialise each operational decision, rather than adjusting every decision to a fixed spatial pattern. This concept should be very amenable to high-value perennial horticultural systems where each plant has a large spatial footprint, and plant-specific management is a potential reality.

To achieve this, research should be directed to developing better site-specific decision processes (and zoning) rather than adapting the conventional notion of management units to horticulture management. This will require development in several areas including i) better methods for input data selection based on the type of decision being made, ii) methods to correctly formalise objectives within the constraints of the production system and, iii) how to properly capture and use local and expert knowledge for decision zoning to achieve the objectives. This will invariably require

some trade-off between automated processes and the need to easily incorporate the grower's knowledge into the decision system. What are the most suitable technologies to achieve this and what is the role of natural language programming if this space is to be shared by both agronomists and computer scientists? For site- and plant-specific management to be successful in the future, these will be key questions to answer, as it is likely that the most effective decisions will come arise from interactions between growers/agronomists and computer scientists/models.

However, the concept of management units has been used for more than data fusion and for informing zone-specific management in precision agriculture. The delineation of management units has also been useful in advancing spatial crop modelling, for redesigning on-farm experiments and for interrogating spatial relationships within agricultural data sets. For horticulture, these uses of management units should remain highly valuable, especially for industries and for producers who are entering into the precision horticulture domain. Under such circumstances, data/information availability as well as the knowledge of spatial relationships between crop, soil and management are likely to be limited. Delineating and using management units will remain an invaluable production tool until such knowledge is accrued and data/information availability increases sufficiently to populate spatial site-specific decision processes.

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