OPTIMAL PLACEMENT OF PROXIMAL SENSORS FOR PRECISION IRRIGATION IN TREE CROPS

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Abstract. In agriculture, use of sensors and controllers to apply only the quantity of water required, where and when it is needed (i.e., precision irrigation), is growing in importance. The goal of this study was to generate relatively homogeneous management zones and determine optimal placement of just a few sensors within each management zone so that reliable estimation of plant water status could be obtained to implement precision irrigation in a 2.0 ha almond orchard located in California, USA. First Fuzzy C-means algorithm was used to create management zones using stable soil properties. Following the creation of management zones, a slightly modified Fuzzy C-Means algorithm was used to choose the best places to locate the leaf monitors, a specially developed sensor to detect plant water status, in the field. The methodology and algorithm allowed not only the generation of efficient management zones based on soil and plant characteristics, but also the placement of a limited number of sensors within each management zone to capture spatial variability in plant water status. The algorithm can also be helpful in placement of proximal sensors in field crops.

Keywords.*Precision Irrigation, Almond, Management Zones, Sensor Placement.*

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Introduction

While climate change and weather conditions are causing a shortage of water resources worldwide, the demand for water for industrial, domestic and agriculture uses continues to increase (Fischer et al., 2007). Therefore, it is imperative to conduct research aimed at optimizing the use of water (Nijbroek et al. 2003), especially in high demand sectors, such as agriculture. Irrigation is applied in areas where natural rainfall is insufficient to meet the crop water requirements during the growing season. Irrigated agriculture, which is one key factor for feeding the growing world population, is responsible for 70–80% of the total water usage in the arid and semi-arid zones (Fereres and Soriano, 2007). In these areas, food production depends on the availability of sufficient amounts of water in a timely manner on a site-specific basis to ensure quality and quantity of production (Camp and Sadler 1998).

A management zone (MZ) is a sub-area where there is relative homogeneity in potential crop production due to similar soil nutrients and environmental effects caused by similar landscape or soil conditions (Yan et al. 2007). A MZ has similar characteristics of soil and topography, and therefore, requires similar amounts of agricultural inputs such as water and nutrients (Moral et al. 2010; Schepers et al. 2004). The delineated zones can be considered as separate zones for soil–water management, allowing optimization of water resources during land preparation and irrigation (Islam et al. 2011).

The Fuzzy C-Means algorithm has been widely accepted as a useful tool to create MZs (Iliadis et al. 2010; Arno et al. 2011; Valente et al. 2012; Li et al. 2013). In general, it offers good results (Jipkate and Gohokar, 2012; Mingoti and Lima, 2006) and creates zones automatically and in a non-subjective way (Fridgen et al. 2004). Moreover, it allows the division of a data set into C-clusters, with reference to a center of mass or centroid for each cluster (Fridgen et al. 2004). Furthermore, the statistics associated with Fuzzy C-Means, the fuzziness performance index (FPI) and the modified partition entropy (MPE) help to define the best number of clusters or zones for each field.

The objective of this research was to develop a methodology to define the best locations to install proximal sensors to provide a representative mean value of a given attribute within each management zone, accounting for spatial variability. To create MZs, soil texture, Elevation (Elev) and Electrical Conductivity (ECa) data was used and to select the best placement to put the leaf sensor in the field Stem Water Potential (SWP) was used.

Methodology

One almond orchard field of 2.0 ha located in Arbuckle, CA (coordinates of the grid center are 38°57'59.14"N, 122° 4'24.97"W) was selected for the experiment. Fifty (50) soil samples were taken throughout field in a regular grid 5 x 10 m for soil characterization (digital elevation and texture analysis).

In addition, the ECadata, obtained at two soil depths (0.3 and 0.9 m) using Veris model 3100 sensor system (Veris Technologies of Salina, KS, USA) were included because they have been found to have a good relationship with soil textural characteristics (Sudduth, et al., 2005) and have proven useful for delineation of management zones (Peralta and Costa, 2013; Moral et al., 2010).

As the grid sizes were different - sparse data (texture and elevation) with 50 samples and dense data (ECa) - the geostatistical analysis and kriging were performed for these attributes to obtain interpolated values of these attributes for each tree. Then, the Fuzzy C-Means Algorithm was used to create MZs (Figure 1).

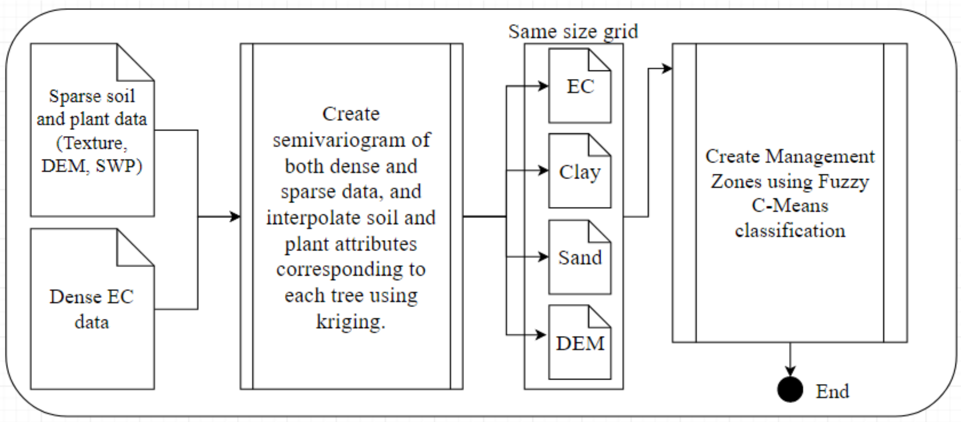

Fig. 1 Flowchart of steps to create management zones

For interpolating data, defining classes, and delineating MZ maps, the software SDUM (Software to Definition Management Units) (Bazzi et al. 2013) was used. The software uses ordinary kriging as the interpolation method with pixels with an area of 2 x 2 m and 10 neighbors. After interpolation, resulting data were used as the input for the Fuzzy C-means algorithm (Bezdek, 1981), by selecting error parameter equal to 0.0001, and weight index equals to 1.3. In evaluating the optimal number of clusters, SDUM provides the possibility of using three different methods, (equations 1 to 3):

1. Variance Reduction – VR (Dobermann et al. 2003; Xiang et al. 2007):

$$VR = 1 - \frac{\sum_{i=1}^{n} W_i * V_{um_i}}{V_{field}} * 100 \quad (1)$$

where, n – sample size in the entire area; W_i – proportion of the area in each management unit; V_{um_i} – variance of data in each management unit; V_{field} – variance of the data sample for the whole field.

2. Fuzzyperformance index – *FPI* (Fridgen et al., 2004):

$$FPI = 1 - \frac{c}{(c-1)}\left[1 - \sum_{j=1}^{n}\sum_{i=1}^{c}(u_{ij})^2 / n\right] \quad (2)$$

where, c – number of clusters; n – sample size in the whole area (number of observations); u_{ij} – element *ij* of the relevant Fuzzy matrix.

3. Modified partition entropy index– *MPE (*Boydell and Mcbratney 2002):

$$MPE = \frac{-\sum_{j=1}^{n}\sum_{i=1}^{c} u_{ij} \log(u_{ij}) / n}{\log c} \quad (3)$$

where, c – number of cluster; n – sample size in the whole area (number of observations); u_{ij} – element *ij* of the relevance Fuzzy matrix.

The best location for each leaf sensor that is a part of a set of sensors used to represent that zone was defined using the Fuzzy C-Means algorithm with some modifications. Statistically, the

Fuzzy C-means algorithm minimizes the sum of squares of errors within each class following some criteria and the data are grouped iteratively to the nearest class using the minimum distance criterion. The method assumes a data set $X = \{x_1, x_2, ..., x_n\}$ where x_k corresponds to a features vector $x_k = \{x_{k1}, x_{k2}, ..., x_{kp}\} \in R^P$ for each $k \in \{1,2,...n\}$ where R^P is the p-dimensional space. The aim is to find a pseudo partition Fuzzy set that corresponds to a family of C Fuzzy sets of X, which best represents the data structure and is denoted by $P = \{A_1, A_2, ..., A_C\}$ and satisfies $\sum_{i=1}^{c} A_i(x_k) = 1$ and $0 < \sum_{k=1}^{n} A_i(x_k) < n$, where $k \in \{1,2,..,n\}$ and n represents the number of elements of X. The algorithm is characterized by the grouping number (C), a distance measurement that defines the allowed distance between the points, and the centroid $(m \in (1,\infty))$.

The position of each centroid was calculated considering the grouping number, C. For each C, $v_1^{(t)},..v_c^{(t)}$, equation (4) was evaluated iteratively for the partition $P^{(t)}$, where $t = \{1,2..,n\}$ is the iteration number. The vector v_i corresponds to the grouping center A_i (equation 5) and is the weighted average of the data in A_i. The value of the data x_k is the *m-th* power of its relevance degree to the Fuzzy set, A_i.

$$v_i = \frac{\sum_{k=1}^{n} [A_i(x_k)]^m x_k}{\sum_{k=1}^{n} [A_i(X_k)]^m} \tag{4}$$

$$A_i^{(t+1)}(x_k) = \left[\sum_{j=1}^{c} \left(\frac{\| x_k - v_i^{(t)} \|^2}{\| x_k - v_j^{(t)} \|^2} \right)^{\frac{1}{m-1}} \right]^{-1} \tag{5}$$

where, $\| x_k - v_i^{(t)} \|^2$ represents the distance between x_k and v_i.

In this study, we consider a particular proximal sensor called leaf monitor developed at UC Davis to measure plant water status. It consists of a suite of sensors that measure leaf temperature, air temperature, relative humidity, incident radiation and wind speed and relate these data to plant water status as represented by stem water potential (SWP) (Dhillon et al., 2018). As leaf monitors must be placed on trees, all combinations of tree locations (i.e., ($T_1 - T_2, T_1 - T_3,.., T_1 - T_n, T_2 - T_3,.., T_{n-1} - T_n$, where symbol T_i stands for the i^{th} tree) were used in the calculation of the centroid. All possible combinations were tested and corresponding FPI and MPE indexes (equations 2 and 3) were evaluated.

Stem water potential (SWP), measured using a pressure chamber, was usedto determine the best locations for leaf monitors to measure plant water status within a management unit, where the lower values of FPI and MPE were used to find the optimal locations for different scenarios (i.e., locating one, two, three, or four sensors in a MZ).

Results and discussion

Following the recommendation by Doerge, (2000), Stable soil properties of soil texture, digital elevation along with ECa were used to create management zones. A specially developed software by Bazzi et al. (2013) known as SDUM was used to generate 2, 3, 4 and 5 classes (Figure 2). The FPI and MPE indices were lowest when the fields were divided into two classes, indicating that two zones are optimal for this field (Figure 3).

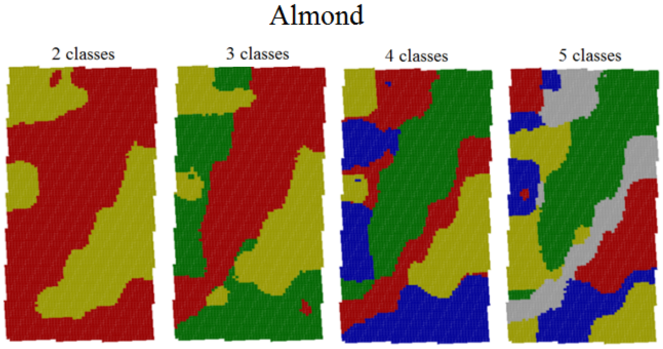

Fig. 2. Management zones created using Fuzzy C-Means clustering

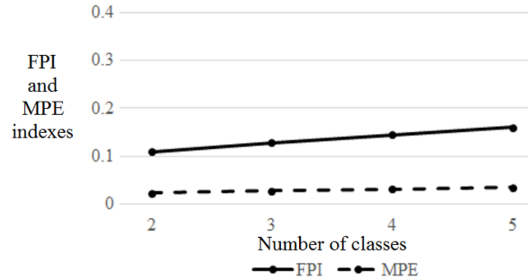

Fig. 3. FPI and MPE indices when field was divided into 2, 3, 4 and 5 MZs.

The variance decreased significantly for all attributes when only two management zones were included (Table 2). These results show that the division of each field into two management zones was justified as it reduced variance and increased uniformity of attributes within each zone.

Table 2.Descriptive analysis of attributes for each zone in almond field

Variable	Zone	N S.	Min	Mean	Max	SD[1]	CV(%)[2]	VR(%)[3]
Clay	1	158	6.20	8.65a	10.41	0.88	10.17	21.9
	2	94	8.01	9.68b	12.03	1.01	10.43	
Sand	1	158	67.68	73.67a	79.11	2.45	3.33	45.7
	2	94	64.06	68.77b	74.85	2.82	4.10	
Silt	1	158	13.59	17.69a	23.28	2.05	11.59	42.5
	2	94	16.62	21.55b	25.22	2.38	11.04	
Elevation	1	158	55.24	56.70a	57.98	0.68	1.20	13.0
	2	94	55.34	56.17b	57.31	0.59	1.05	
ECa_0.3	1	158	4.63	6.58a	10.17	1.15	17.48	67.9
	2	94	7.53	11.83b	16.29	2.46	20.79	
ECa_0.9	1	158	8.27	12.52a	20.50	2.65	21.17	69.8
	2	94	13.25	23.22b	30.91	4.43	19.08	
SWP	1	158	7.43	8.80	10.11	0.48	5.43	1.00
	2	94	7.08	8.78	10.78	0.50	5.63	

[1] Standard deviation; [2] Coefficient of variation; [3] Variance reductions. NS Number of samples

The distribution of centroids values when the SWP attribute was considered to select the best positions to install the leaf sensors within each MZ(Figure 4), shows that the Fuzzy C-Means was efficient in finding distinct locations to install the leaf sensors.

When only one sensor was to be installed for each field, the selected tree was the one closest to the mean location. However, placement of only one sensor can be risky, since sensor failure can lead to total information loss.We looked at the possibility of installing 2, 3, or 4 sensors also and how the number of sensors and their locations affected the overall behavior of the management zone.

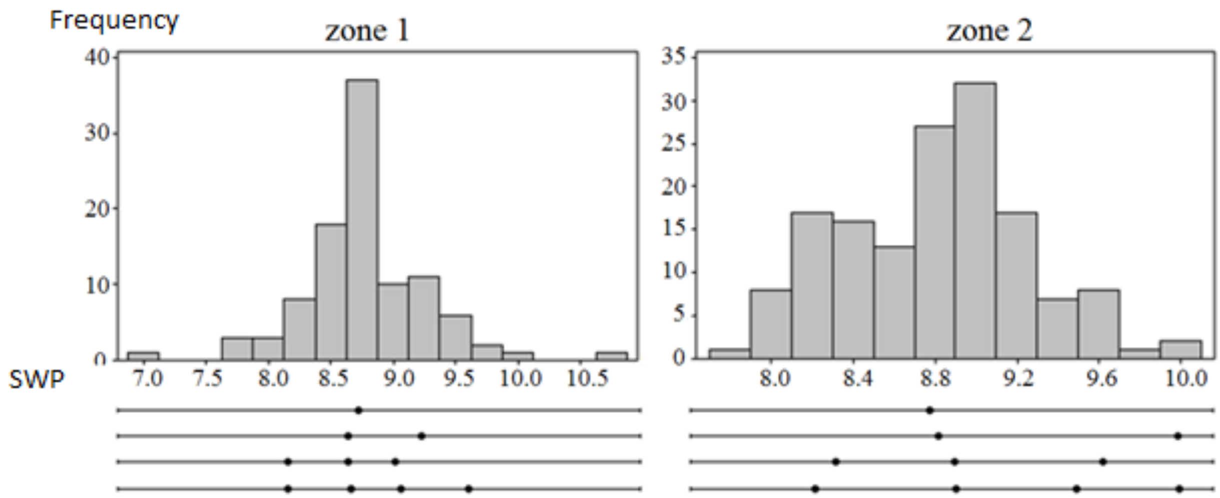

Figure 4. Histogram of SWP attribute and values of the trees chosen to install the sensors in almond orchard for zone 1 and 2.

The Figure 5 shows the location of trees chosen to install sensors and FPI and MPE indices when two, three, and four sensors were to be installed. It is important to select the most representative attribute (in this case SWP) to decide where to install leaf monitors. For all cases, the best number of sensors were two for each zone. However, from a statistical point of view, at least three sensors should be installed within a management unit.

The proposed method is attractive to help select the number of sensors and the best locations to install them in the field considering the investment required for monitoring fields.

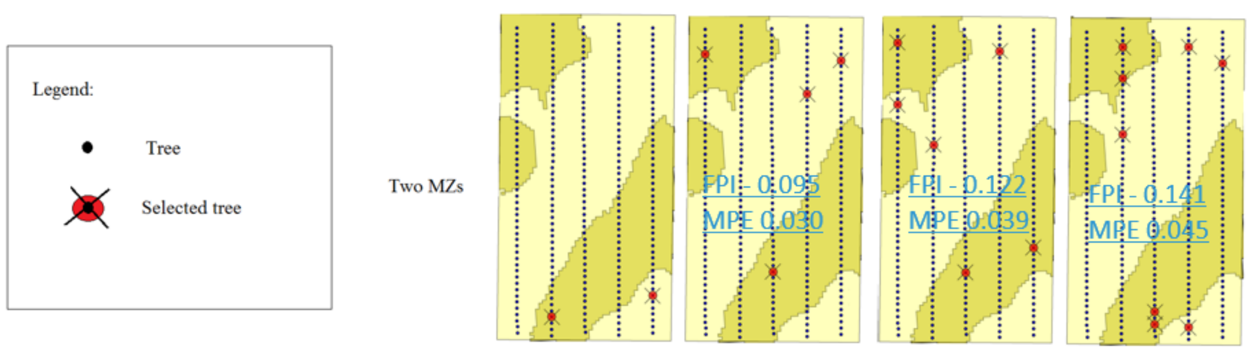

Fig 5. Location of leaf sensors when SWP data were used to select the trees to install them, considering the number of sensors and MZs, showing FPI and MPE indices

CONCLUSIONS

In this study, the possibility of creating management zones within an orchard to implement precision irrigation and determine optimum locations for installing a limited number of proximal sensors (leaf monitors) for determining plant water status, was explored, and the following conclusions were reached:

- Fuzzy C-means algorithm was successfully used to delineate management zones. This technique led to two relatively homogeneous zones with significantly lower variability in the attributes within each zone for a 2 ha almond orchard in Arbuckle, CA.
- The Fuzzy C-Means algorithm was modified to determine optimum locations for installing proximal sensors within a management zone. The procedure was illustrated using data obtained in an almond orchard to install leaf monitors capable of determining plant water status. The results indicated that just two sensors placed at the right location can be sufficient to provide reliable information about each management zone, but three

sensors would be preferable from a statistical point of view. Although the technique was applied to leaf monitors, the technique is applicable to other proximal sensors also.

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