Coupling Macro and Micro-scale Variability for Delineation of Site-Specific Management Grid

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Abstract

Quantifying variability in soils often provides a macro-scale characterization of soil properties. Conversely, high-resolution reflectance-based characterization of crop canopy has enabled quantification of crop characteristics at a micro-scale. This study aims to delineate a site-specific management unit that accounts for both macro-scale spatial variability in soil and micro-scale spatial variability in crops. The specific objective of this study was to generate H-FIS based Site-Specific Management Grids that accounts for macro and micro variability in soil and crop properties. The study was conducted over four site years at Kansas River Valley (KRV) experimentation fields in Topeka and Rossville, Kansas. A proximal soil sensor, Veris-MSP3 was used to acquire soil variables. The Unmanned Aerial Vehicle (UAV) on-board MicaSense Rededge-3 multispectral sensor was used to collect multi-spectral images. These imageries were subsequently processed to calculate vegetation indices including NDVI (Normalized Difference Vegetation Index), SAVI (Soil Adjusted Vegetation Index), NDRE (Normalized Difference Red Edge) as proxy to crop growth. The H-FIS output data were used to map the SSMGs. A classification with ten classes of grid-based management units was successfully delineated for all site years. A similar spatial trend was observed between coupled variable SSMGs and grain yield (corn and soybean) for all site years. The degree of agreement between coupled soil-crop variables based SSMGs and solely macro-scale variability based SSMGs indicated a dissimilarity with

kappa coefficient (κ) ranging between -0.013 and 0.16. Overall, the complex coupling of soil and crop variables accounting for both macro- and micro-scale variability was achieved.

Introduction

Soil-based Site-Specific Management Zone (SSMZ) guided variable rate fertilizer applications were found to be efficient for areas with large-scale spatial variability of soil properties (Cordero et al., 2019). Several methods have been proposed to delineate management zones based on soil properties (Derby et al., 2007; Peralta et al., 2015; Haghverdi et al., 2015; Tripathi et al., 2015; Gili et al., 2017; Rossi et al., 2018, topographic attributes (Fraisse et al., 2001), and remote sensing data over bare soil (Georgi et al., 2018; Mulla, 2013), all of these methods accounted primarily macro-scale variability in soils. Accounting only macro-scale variability in soil for management units is not sufficient because it fails to account for in-season crop nitrogen (N) demand influenced by weather and crop management practices (Shanahan et al., 2008). Even though quantifying micro-scale variability has been studied with crop N sensors, there are very few studies that tried to integrate macro-scale and micro-scale variability for delineation of a site-specific management unit. The delineation of management units can consider a spectrum of possibilities and their respective likelihoods, moving away from single deterministic prediction. Such an approach provides more precise management units, tailored based on grid size applicable for farm implement width and also accounts for macro and micro-variability in the system. Considering the size of these smaller management units to match individual nozzle level fertilizer delivery system, these management units are more appropriately referred to as 'Site-Specific Management Grid (SSMG)'. The objective of this study was to generate fuzzy inference system based site-specific management grids that accounts for macro and micro variability in soil and crop properties.

Materials and Methods

This study was conducted over a period of two years (2021 and 2022) at two locations in Kansas, over a total of four site-years. The sites are distributed across Kansas River Valley (KRV) experiment fields at Topeka (39° 4’ 34.04"N, 95° 46’ 11.98"W) and Rossville (39° 7’ 6.36"N, 95° 55’ 37.35"W) stations. Studies conducted at KRV Topeka experiment field were designated as ‘site year-1’ and ‘site year-2’ for 2021 and 2022, respectively, and studies conducted at KRV Rossville experiment field were labelled as ‘site year-3’ and ‘site year-4’ for 2021 and 2022, respectively. Trimble *Real-time kinematic* positioning (RTK) system equipped, John Deere 5055E tractor was coupled with Veris-MSP3 (Veris Technologies, Inc., Salina, KS, USA) system to acquire apparent soil Electrical conductivity at depth of 0-30 cm (ECa shallow), apparent Electrical conductivity at depth of 0-90 cm (ECa deep) and organic matter (OM). Aerial imagery was collected with a MicaSense Rededge-3 multispectral sensor (MicaSense, Seattle, WA, USA) mounted on a DJI Matrice 100 quadcopter (DJI, Nanshan, Shenzhen, China) unmanned aerial vehicle (UAV). The multi-spectral sensor has 5 wavebands: Blue (475±20 nm), Green (560±20 nm), Red (668±10 nm), Red Edge (717±10 nm), and Near-infrared (840±40 nm). Imageries collected on each flight date were processed with Pix4D mapper Pro software (Pix4D, Lausanne, Switzerland) to create georeferenced and orthorectified mosaic images. Vegetation indices were calculated with Pix4D mapper index calculator tool using the respective band reflectance. Multi-spectral images collected for the study sites were processed to generate NDVI (Normalized Difference Vegetation Index), SAVI (Soil Adjusted Vegetation Index), NDRE (Normalized Difference Red Edge), and DSM maps. A total of seven to eight soil and crop variables that influenced spatial variability of yield were selected per site-year to develop fuzzy logic system. For each site-year, soil and topography variables including, DSM (m), slope (%), ECa (mS/m) at shallow, ECa (mS/m) at deep depth, OM (%), and CEC in addition to one or two vegetation indices (NDVI, SAVI, and NDRE) used as input variables and their respective yield/productivity as an output variable. ANFIS tuned MFs were used as an input to develop H-FIS model. The H-FIS model executed with a scripted Matlab code using "evalfis" function and compute fuzzification output as a result. The Takagi-Sugeno fuzzy inference system was employed to compute the outputs. The fuzzy outputs were classified into 10 quantile-based interval classes of grid-based site-specific management maps using ArcGIS Pro 3.1.1 software. A reclassification of the 10 class was made indicating 10 (dark green) as a potentially high management grid and 1 (dark red) as a potentially low management grid.

Results

H-FIS based SSMGs using coupled soil and crop input variables are shown in Figure 1 a and b, for site year-1 and 2. SSMG classes show grid productivity scales, denoting 10 as high productive grid and 1 as low productive grid. For site year-1, a noticeable low productivity grids occupied the centre of field encapsulated by a medium productivity grids and high productivity grids bounding the medium productivity grids (Figure 1 a). On the contrary, for soybean cultivated site year-2, a high-productivity grids seem more dominant compared to site year-1 SSMG (Figure 1 b) and the low-productivity grids appears to have shrunk in number of grids and divided into smaller regions. Visually, coupled macro-scale and micro-scale variability based SSMGs presented both macro-scale and micro-scale variability in the delineated SSMGs (Figure 1 a and b), whereas soil based SSMGs only captured macro-scale variability (Figure 1 c and d).

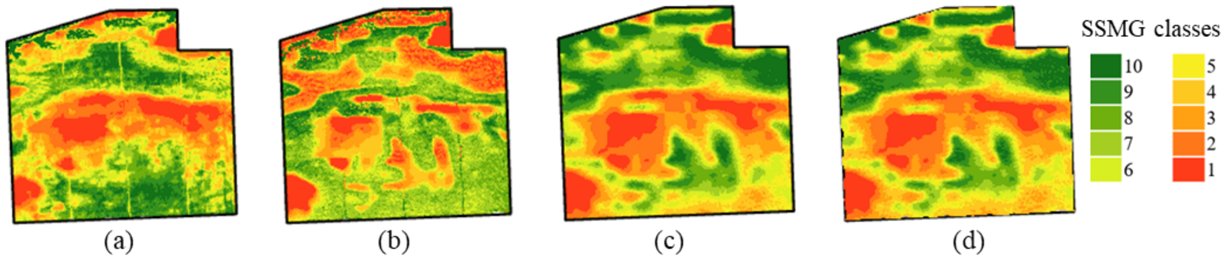

Figure 0. Hybrid-Fuzzy Inference System (H-FIS) based site-specific management grids with coupling of macro-scale spatial variability in soil and micro-scale variability in crop for (a) site year-1, (b) site year-2; and site-specific management grids with soil alone for (c) site year-1, (d) site year-2.

The effectiveness of H-FIS in accurately mapping human thought processes and argumentations significantly advances the process of micro- and macro-scale variability data fusion (multi-scale data fusion). The rule-based inference engine of H-FIS allowed different types of data to be related to each other and their information content is enhanced. The significant finding of this study is that an integration of macro- and micro-scale variability for delineation of SSMGs, increased number of high and medium productivity grids for all site years. The visual observation of H-FIS based SSMGs were supported by quantitative assessment with kappa coefficient (κ) based on the agreement between the SSMGs. Quantitative comparison between coupled variables based SSMGs and macro-scale variability based SSMGs, for both site year-1 and site year-2 reported a kappa coefficient of 0.16 and -0.013, demonstrating the dissimilarities between SSMGs. The kappa coefficient explicitly shows that there was no agreement between SSMGs maps, indicating a dissimilarity created based on the data sources used for delineating the management grids.

Conclusions

The H-FIS delineated site-specific management grid for all study site years. Soil and crop variables-based H-FIS management grid characterized macro-scale variability in soil and micro-scale variability in crop. Scattering of management grids are highly dependent on vegetation indices, as a result there is a clear indication of changes of management grid as changes of crops cultivated. In conclusion, SSMGs successfully translated coupling of macro-scale variability in soil and micro-scale variability in crops to clustered zones that require similar management practices. Delineation of SSMGs is the initial stage in optimizing fertilizer usage and successful SSMGs guided fertilizer applications.

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