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Variable Fertilizer Recommendation for Grass Production by Image–based Growth Status

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Mowing and fertilizer application are important field operations for proper grass growth management. Because grass growth is not uniform across fields, variable rate fertilization may be an effective method for achieving high grass yields and enhancing fertilizer use efficiency. The objective of this research was to recommend variable rate fertilization for sod production fields depending on site–specific grass growth levels estimated by CCD camera images. CCD images were acquired from three different sod production fields and calibration relationships were obtained between the sensor measurements and the grass growth levels. Based on the calibrations, fertilizer application rates were site–specifically recommended based on expert experience. The grass growth levels and the fertilizer requirements were mapped for the three fields through geostatistical analyses. For the analysis of the spatial variation of growth level and mapping, geostatistical methods such as variogram modeling and Kriging interpolation were used. Linear relationships were obtained for the calibrations between the image–processed results and grass growth levels. Inverse linear relationships between fertilizer recommendations and grass growth levels were obtained with R^2 of 0.966, 0.971, and 0.944 for 90%, 70%, and 50% grass growth coverage fields. Exponential models were found to best fit data for 90% and 50% grass growth coverage fields with R^2 of 0.843 and 0.780, respectively. Whereas, a spherical model was found to best fit data for 70% growth grass coverage field with R^2 of 0.968. Turfgrass growth levels were divided into 0 (0%) to 10 (100%) levels, and accordingly, fertilization levels of 10 (100%) to 0 (0%) levels were recommended. The interpolated maps showed a recommended fertilizer application range of 0.5 (5%)~1.0 (10%), 0.5 (5%)~1.5 (15%), and 2.0 (20%)~ 4.0 (40%) levels in the middle areas for 90%, 70%, and 50% growth coverage fields, respectively. Whereas, ranges of 3.5 (35%)~4.7 (47%), 3.0 (30%)~4.0 (40%), and 2.0 (20%)~3.0 (30%) levels were recommended in the edge areas of 90%, 70%, and 50% growth coverage fields, respectively. This study could contribute to increase fertilizer use efficiency, reduce environmental contamination, and improve grass quality and growth if the recommended fertilizers are variably applied.

Key words: precision agriculture, grass growth, image processing, variable fertilizer recommendation, geostatistics

INTRODUCTION

Sod production has increased in developed and developing countries as a profitable alternative to many traditional agricultural enterprises (Aldous *et al*., 2007; Yi, 2012). The turfgrass–sod industry is growing rapidly due to strong demand as a result of its functional, recreational, and aesthetic benefits in urban landscapes (Haydu *et al*., 2006; Monteiro, 2017). The sod cultivation area in Korea has increased by 3,056 ha (17.8%) in 2011 compared to sod production in 2006 (13.6%) (Choi and Yang, 2006; Korea Forest Service, 2012; Youn *et al*., 2005; Youn *et al*., 2006).

Mowing is one of the key cultural practices for producing a healthy, dense stand of turf as mowing too low or even too high could stress the turfgrass. Fertilization is also an important issue for turf growth management and has a major influence on achieving a balance between shoot growth and root development of the transplanted sod (White *et al*., 1991) as excessive nitrogen rates retard root development of the transplanted sod (Duble, 2001). Applying the right amount of nitrogen at different locations in the field is very important for healthy plant growth (Bean *et al*., 2012). Otherwise growth would not be uniform, showing better growth in some parts and less growth in other parts of the field.

Variable rate fertilization (VRF) has been an important issue in precision agriculture, and an emerging need for reducing the cost of production and environmental contamination (Ruicheng *et al*., 2013). It allows the farmer to apply different rates of fertilizer at each location across fields to satisfy site–specific management requirements (Koch *et al*., 2004; Farooque *et al*., 2012; Huang *et al*., 2013). This VRF technique can improve fertilization efficiency and protect the environment, and can be achieved by adjusting the application rate based on an electronic map or real–time sensor–based measurement of a continuous stream of information (Grisso *et al*., 2011). Several studies have been reported on the application of VRF in precision agriculture (Murdock and Howe, 1997; Wells and Dollarhide, 1998; Chan *et al*., 2002; Ying–zi *et al*., 2015; Reyes *et al*., 2015; Gourevitch

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et al., 2018). The implementation of VRF depends on the characterization of spatial variability within a field. Therefore, geostatistical analysis was performed to assess the spatial variation of grass growth of the sod production fields.

For successful VRF, sensing of crop growth, understanding the variability, and application recommendations should be established. Fricke *et al*. (2011) used an ultrasonic sensor to measure sward height and predicted forage mass with mean residuals ranged between 0.893 and 1.672. Pittman *et al*. (2015) examined a combination of sensors (laser, ultrasonic, and spectral) for the estimation of biomass yield and plant height in several forage species. Image processing is a popular method to estimate crop growth in different fields of agricultural applications. The texture of an image is a function of the spatial variation in pixel intensities (Tuceryan and Jain, 1998) and is easily perceived by humans (Rosenfeld and Kak, 1982). Some aspects of texture are readily extracted and expressed in numerical form (Chan and McCarty, 1990). Philipp and Rath (2002) compared different transformations of RGB color spaces, and logarithmic discriminant analysis was found to be the most effective method for separating plants and background in color images taken by a digital photo camera. Research on weed/corps discrimination for automatic identification with real–time image processing has also increased recently. Image processing for weed detection is mostly done in two steps, such as segmentation of vegetation against the background (soil and/or harvest residues) and detection of the vegetation pixels that represent weeds (Burgos–Artizzu *et al*., 2011). In segmentation procedures of vegetation, all pixels belonging to vegetation can be easily extracted by some combination of the color planes on the RGB model (e.g., Woebbecke *et al*., 1995; Andreasen *et al*., 1997; Pérez *et al*., 2000; Aitkenhead *et al*., 2003; Yang *et al*., 2003; Ribeiro *et al*., 2005; Van Evert *et al*., 2006). The performance of potential sensors such as CCD cameras, ultrasonic modules, and optical reflectance sensors were compared for grass growth estimation under different turfgrowth levels and sensor operation conditions by Kabir *et al*. (2016). The CCD camera proved to have the feasibility of grass growth detection in different operating conditions.

Variability analysis and mapping of grass growth could be used to reflect the need for fertilization in a turfgrass growing area. Research has been conducted to develop spatial variable fertilization systems for different crops (Raun *et al*., 2005; Basso *et al*., 2011; Basso *et al*., 2016; Farooque *et al*., 2012; Xu *et al*., 2015; Ha *et al*., 2015). Xu *et al*. (2014a, 2014b) developed a *Nutrient Expert (NE) for Hybrid Maize* fertilizer recommendation system, a promising nutrient decision support tool, that not only increased grain yield, nutrient use efficiency and profit, but also reduced nutrient loss and environmental pollution. Liu *et al*. (2017) proposed a method for formulating recommended fertilizer rates for rice using agronomic efficiencies and a sustainable yield index (SYI), and recommended mean N, P_2O_5, and K_2O fertilization rates of 186, 60, and 96 kg/ha, respectively, in the study region. Carey *et al*. (2012) documented turfgrass fertilization practices such as the proper combination of fertilizer rate, timing, and placement that maximized nutrient utilization efficiency and their impacts on urban water quality. Efficient grass growth mapping can be useful for the implementation of timely and site–specific fertilizer management for high–quality turfgrass growth. Based on the maps, a grass field can be divided into different zones to allow growers to use different techniques according to the conditions in each area of the grass field. The fertilizer application maps are useful to indicate the amount of fertilizer required in each zone, and variable rate fertilization could be used to apply the average rate of fertilizer in each zone of the field.

The objective of this study was to recommend variable rate fertilization for sod production fields with grass coverage density of about 90%, 70%, and 50%, based on site–specific grass growth levels estimated by CCD camera images.

MATERIALS AND METHODS

Concept of the variable rate fertilizer recommendation

The concept of variable rate fertilizer recommendation using image sensor–based turfgrass growth mapping is shown in Fig. 1. This map–based variable rate fertilization consists of three parts: sensing of turfgrass growth information, interpolation and mapping, and variable rate fertilizer recommendation. In the first step, the turfgrass growth status of three different turfgrass fields covering 90%, 70%, and 50% turfgrass were sensed using an image sensor (CCD camera). Then the images were processed to identify the turfgrass growth status of the field and calibration was done to recommend fertilizer for different turfgrass growth levels. The turfgrass growth maps for each field were derived from image sensor data and the position of the field acquired by a global positioning system (GPS). Finally, variable rate fertilizer was recommended based on the turfgrass growth levels for each of the sod production fields.

Field sites and image acquisition

Grass image sets were obtained for sod production fields in the southern part of South Korea in three different field conditions with grass coverage density of about 90% (720 m^2; 35°15' N, 126°61' E), 70% (900 m^2; 35°16' N, 126°63' E), and 50% (800 m^2; 35°17' N, 126°63' E) reported by a skilled farmer (owner of the farm) who had experience of growing grass for over 10 years. The shapes of the sod production fields, together with travel trajectories in satellite images and the sample images captured by the camera are shown in Fig. 2. The grass variety was *Zoysia Japonica Steud* (Korean lawngrass). In this region of Korea, *Zoysia* grass is usually planted from April to May and harvested from September to October about 15 months after planting. During the *Zoysia* grass growing season in 2013, the average range

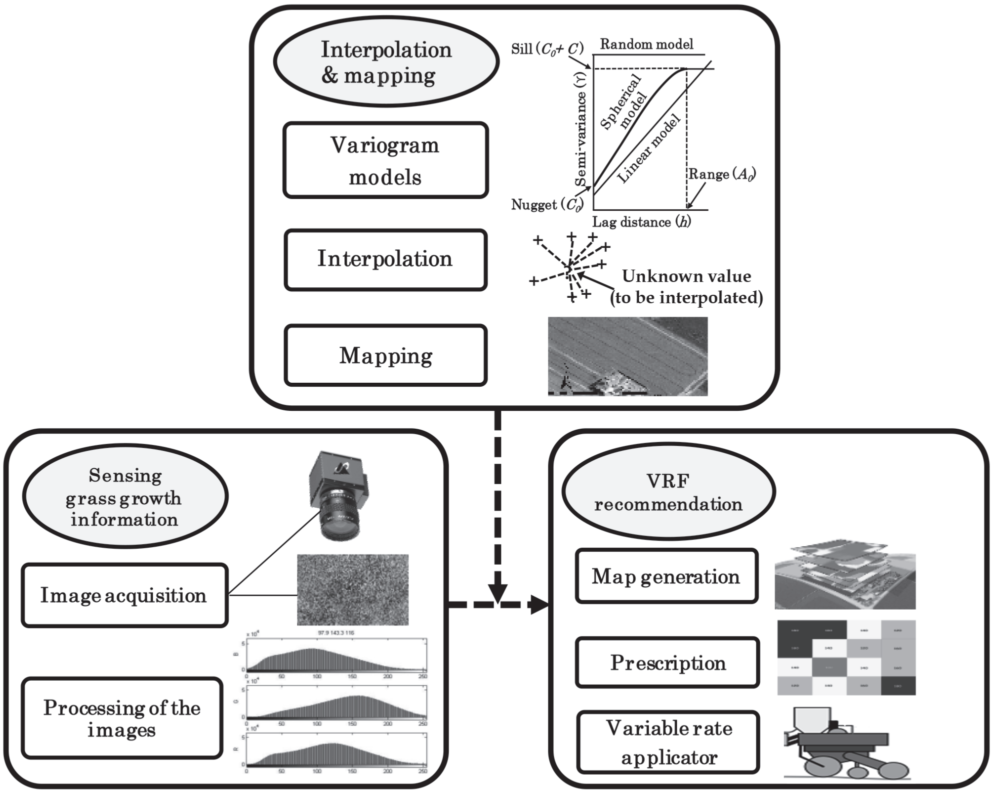

Fig. 1. Schematic diagram showing concept of variable fertilizer (VRF) recommendation based on grass growth maps.

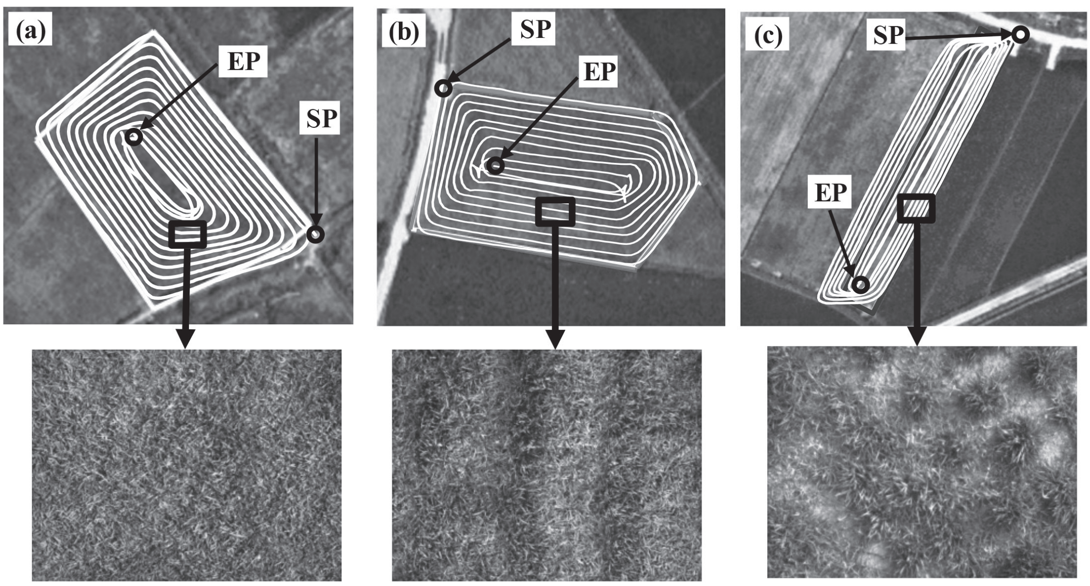

Fig. 2. Grass growth conditions and travel trajectories with starting point (SP) and end point (EP) of growth measurements in three different field conditions: (a) Field 1, 90% growth; (b) Field 2, 70% growth; (c) Field 3, 50% growth.

of monthly temperature and rainfall was 11.4~28.4℃ and 30.8~349.1 mm, respectively. The experiments were performed in the middle of September 2013, and the average monthly temperature was 24.5℃.

In our previous research, a CCD camera was mounted on the top front of a mower tractor at a height of 1.6 m and pointed downward to the ground (Fig. 3). The detection area of the CCD camera was $100 \times 50\ cm^2$ and the images were taken from three fields while driving the tractor at 1–m straight line intervals without stopping. Images were taken at 20 points in each field and calibration was done between sensor measurements and growth levels quantified by a skilled expert (Kabir *et al*., 2016).

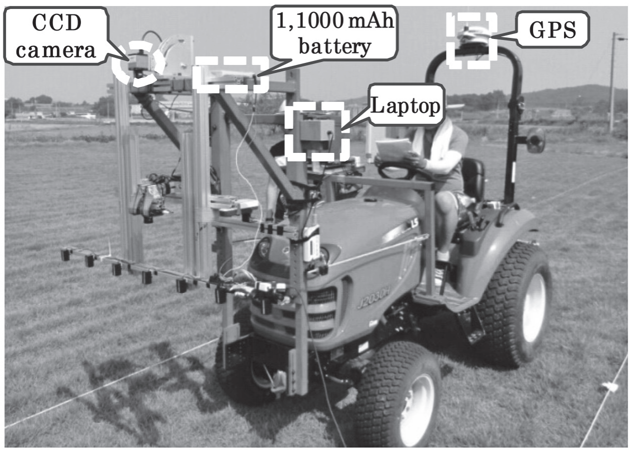

Fig. 3. Grass growth mapping system on the mower tractor.

Therefore, in this research, a CCD camera (model: DFK 31BF03, Sony Co., Japan) with 1280 × 960 resolution was used for taking pictures in turfgrass fields without extra illumination, flash or covering. The camera had a 1/3–inch CCD chip and 4.65 μm × 4.65 μm pixel images were possible as three–channel images in the RGB color space. The specifications of the CCD camera are shown in Table 1. Images were captured from each turfgrass field riding on the mower tractor at a speed of 0.5 m/s together with the position information gathered by a GPS receiver. The camera was connected to a laptop and the LabVIEW program (ver. 2012; National Instruments; Austin, Texas, USA) was used to acquire the images. Position coordinates of the Zoysia grass measuring points were obtained using RTK–GPS (model: A220, Hemisphere GPS Co., USA). All of the data were stored in the computer in real time. The data were then merged by software using the Matlab program (version R2011a, Math Works, USA).

Variable fertilizer recommendation procedure

In our previous research (Kabir *et al*., 2016), grass images were acquired from turfgrass fields with 90%, 70%, and 50% growth coverage during static, vibration, and travelling conditions to reflect the grass coverages. The grass images collected from those three fields were processed through the color image segmentation (CIS) process, which was based on the gray level image segmentation approach (histogram thresholding) in the RGB color space. The excess green index (ExG) defined by Woebbecke *et al*. (1995) was employed for the RGB images and binarized by a thresholding method (Gée *et al*., 2008) to the smoothed ExG images considering the white pixels. Fig. 4 shows the total color image segmentation process such as an original image in the RGB color space of a grass field, excess green index (ExG), and finally thresholded binary image. The percentages of grassless area expressed as CIS values (%) were calculated from the images by taking all white pixel values for determining the grass growth levels. From the image analysis results, the *Zoysia* grass growth levels of the three different sod production fields were divided into 10 levels from 1 (grassless) to 10 (well grown).

Calibration between the image processed results (i.e., CIS (%)) and grass growth levels was done for measuring the grass growths of the experimental sod production fields with 90%, 70%, and 50% grass growth coverage. Based on the calibration between CIS and grass growth levels of three different turfgrass fields, turfgrass growth levels were divided into levels from 0 (0%) to 10 (100%) and inverse relationships were obtained between the growth levels and fertilization recommendations to calculate every point's fertilization levels. Similar to the turfgrass growth levels of the sod pro-

Table 1. Specifications of the CCD camera used for taking images

Sensors	Specifications	
	Model	DFK 31BF03, Sony Co. (Japan)
	Size (mm)	50.6 × 50.6 × 130 (H×W×L)
	Resolution (mm)	1280 × 960
	CCD	1/3” Sony CCD ICX204AK sensor
CCD camera	Camera speed (images/s)	Up to 30
	Interface	IEEE–1394/GigE

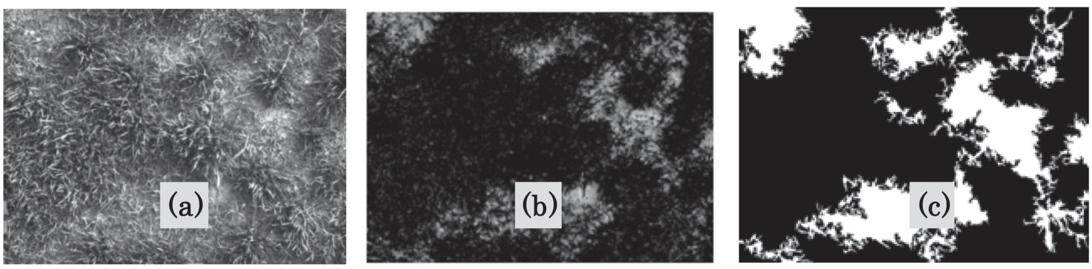

Fig. 4. Steps in image processing for color image segmentation (CIS) calculation: (a) Original image; (b) excess green index; (c) thresholded binary image.

duction fields, fertilizer levels of 10 (100%) to 0 (0%) were accordingly recommended. The inverse linear relationship between fertilizer recommendation (*FR*) and *Zoysia* grass growth (*GG*) was derived by the equation below, where values "*a*" and "*c*" could be selected based on the grass growth status:

$$FR = a \times GG + c$$

The turfgrass growth and fertilizer recommendation maps were created based on the GPS coordinates to reflect the required amount of fertilizer for the target area. Recommended fertilization levels and growth levels of the linear inverse relationship were confirmed by the same variogram results. Those models and coordinates were used and input in GS+ software version 7.0 (Gamma Design Software, Plainwell, Michigan) to create the three fields' growth and fertilization level maps.

Interpolation and mapping

Geostatistical analysis was performed to characterize the spatial variation of the *Zoysia* grass growth using GS+ software. A semivariogram was produced for each of the *Zoysia* grass field to ascertain the degree of spatial variability between neighboring observations. Isotropic models for semivariograms were fitted as no anisotropy evident in directional semivariograms for grass growth. For fitting the semivariogram models, model parameters such as C_0 (nugget effect), C_0+C (sill), A_0 (range), R^2 (coefficient of determination), and RSS (residual sum of square errors) were adjusted. R^2 and RSS were used to select the best models and model parameters were determined.

In the 90% turfgrass growth field, for the semivariance calculation minimum and maximum lag distances were 0.67 m and 20.0 m, respectively. The lag interval was 1.0 m with a minimum number of pairs of 4269. For the 70% turfgrass growth field, the maximum lag distance was 25.0 m with a lag interval of 1.0 m and led to at least 1480 pairs of data points. Whereas, for the 50% turfgrass growth field, the maximum lag distance was 45.0 m with a lag interval of 1.4 m, leading to at least 4099 pairs of data points.

The Kriging interpolation method, which uses semivariograms to express spatial continuity, was used to estimate the values of the selected grass growth properties at unsampled locations and to generate the estimated grass growth and fertilizer recommendation maps from the scattered set of image acquisition points. In this interpolation method, the estimates were based on values at neighboring locations with the spatial relationships. Block Kriging interpolation using 16 neighbor values was done for each of the fields as this value was usually sufficient. The radius values were 49.3, 55.5, and 93.2 for 90%, 70%, and 50% turfgrass growth fields, respectively. The interpolated *Zoysia* grass growth and fertilizer recommendation data were mapped for three different fields from the Kriging analysis. The maps were created with equal intervals of 0.15 m, 0.14 m, and 0.29 m for 90%, 70%, and 50% turfgrass growth fields, respectively.

RESULTS AND DISCUSSION

Grass growth calibration

In our previous research (Kabir *et al*., 2016), the CIS values and grass growth levels of three different turfgrass field showed linear relationships. During the static condition, the CIS values and grass growth levels showed a linear relationship with R^2 value of 0.143, while R^2 value of 0.256 was found for the moving condition. The significance of the slopes of the regression lines was also tested by t–test and no significance differences were found at a 5% significance level.

Based on our previous findings, calibrations between the CIS values (%) and grass growth levels were done for each of the experimental sod production fields with 90%, 70%, and 50% grass growth coverage to quantify the turfgrass growth levels. The turfgrass growth levels of the sod production fields were divided into 10 levels to allow the operator to use an average amount of fertilizer based on the turfgrass growth conditions in each area of the fields. The CIS values were found in a range of 0.32 to 8.8% for the 90% grass growth coverage field with more growth coverage in the range of 5.0 to 10.0 growth levels. A range of 3.5 to 14.0% CIS values was found for the 70% grass growth coverage field with more growth coverage in the range of 4.0 (40%) to 9.0 (90%) growth levels. Whereas, the CIS values were found in a range of 7.5 to 17.5% for the 50% grass growth coverage field with more growth coverage in the range of 1.0 (10%) to 5.0 (50%) growth levels (Fig. 5).

Relationships among grass growth and fertilizer level

Relationships between the image analysis results expressed in CIS (%) and zoysia grass growth level were identified for each zoysia grass field. In the 90% grass growth coverage field, the CIS values and the zoysia grass growth levels exhibited a linear relationship with 85.3% variance. The R^2 value (0.916) was found highest for the 70% grass growth coverage field. Lower accuracy was achieved for the 50% grass growth coverage field with an R^2 value of 0.673. The scatter plots between the CIS value and grass growth (*GG*) level of the three different fields are shown in Fig. 5 (left), and their relationships could be expressed by the following equations:

$$GG_1 = 0.96 \times CIS_1 + 1.4 \quad \text{(Field 1: 90\% coverage)}$$
$$GG_2 = 0.71 \times CIS_2 - 0.21 \quad \text{(Field 2: 70\% coverage)}$$
$$GG_3 = 0.52 \times CIS_3 - 0.74 \quad \text{(Field 3: 50\% coverage)}$$

Where, CIS_1, CIS_2, and CIS_3 are the image processed values and GG_1, GG_2, and GG_3 are the grass growth levels for the 90%, 70% and 50% grass growth coverage fields, respectively.

In addition, inverse linear relationships between grass growth (*GG*) level and fertilizer recommendation (*FR*) were also found for each field. The *Zoysia* grass status was different in the same sod production field; therefore, different levels of fertilization were required. The relationship between grass growth level and ferti-

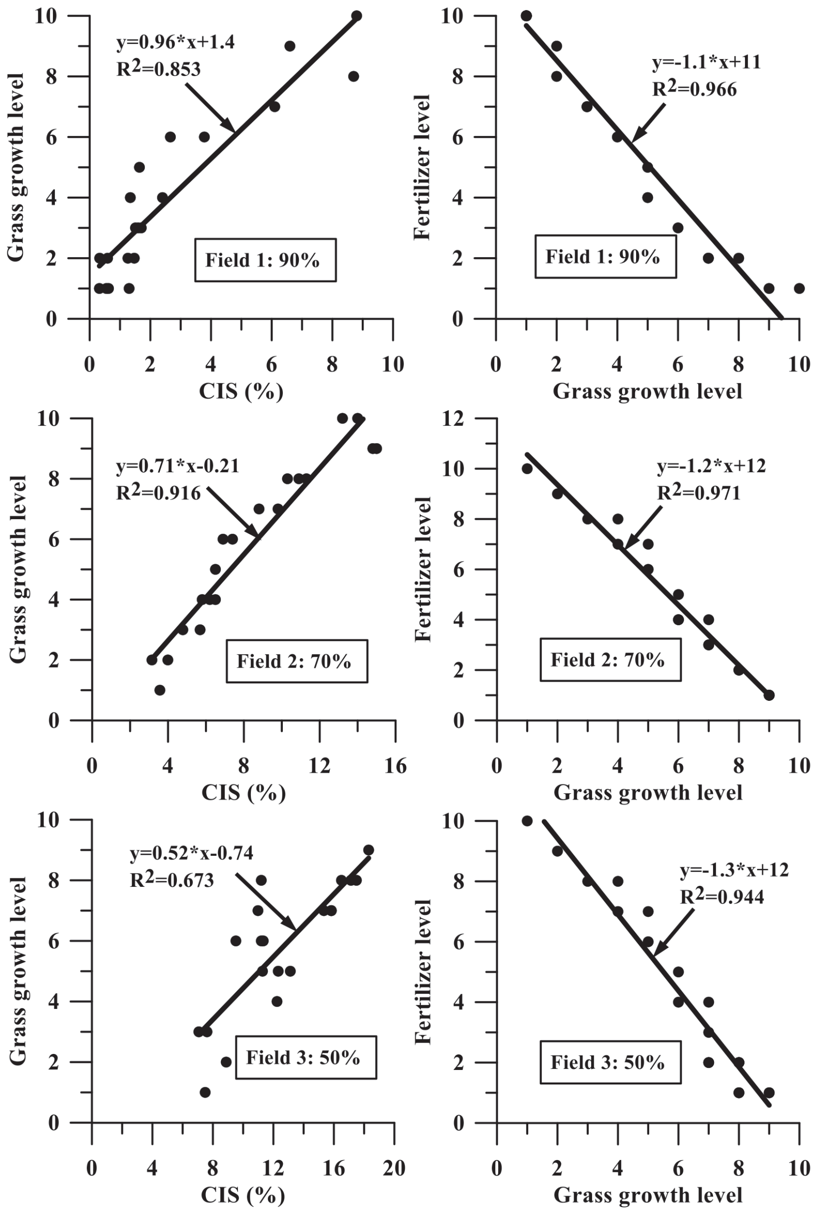

Fig. 5. Relationships between CIS (%) vs. growth levels (left) and grass growth levels vs. fertilization levels (right) for different grass growth coverages.

lizer recommendation exhibited a linear relationship with 96% variance in the 90% grass growth coverage field. Higher accuracy was achieved (R^2=0.971) between grass growth levels and fertilizer recommendation for the 70% grass growth coverage field. Lower accuracy was found for the 50% grass growth coverage field with an R^2 value of 0.944. The scatter plots between the *GG* level and *FR* for three different fields are shown in Fig. 5 (right), and their relationships could be expressed by the following equations:

$FR_1 = -1.1 \times GG_1 + 11$ (Field 1: 90% coverage)
$FR_2 = -1.2 \times GG_2 + 12$ (Field 2: 70% coverage)
$FR_3 = -1.3 \times GG_3 + 12$ (Field 3: 50% coverage)

Where, FR_1, FR_2, and FR_3 are the fertilizer recommendations for the 90%, 70% and 50% grass growth coverage fields, respectively. The fertilizer application maps were prepared according to the grass growth zone maps indicating the variable fertilization required for each zone.

Variability analysis and mapping

The fitted semivariogram models for three experimental fields are shown in Fig. 6. In the 90% turfgrass growth field, the nugget value optimized by different models varied by 0.35% (exponential model) to 0.72% (linear model). The value of sill varied from 0.92% (linear to sill model) to 1.03% (linear model). The optimized range values varied widely, from 1.90 m (exponential model) to 19.50 m (linear model). For the 70% turfgrass growth field, the nugget values were optimized by different models varying from 0.64% (exponential model) to 0.96% (linear model). The value of sill varied from 1.41% (linear to sill model) to 1.56% (linear

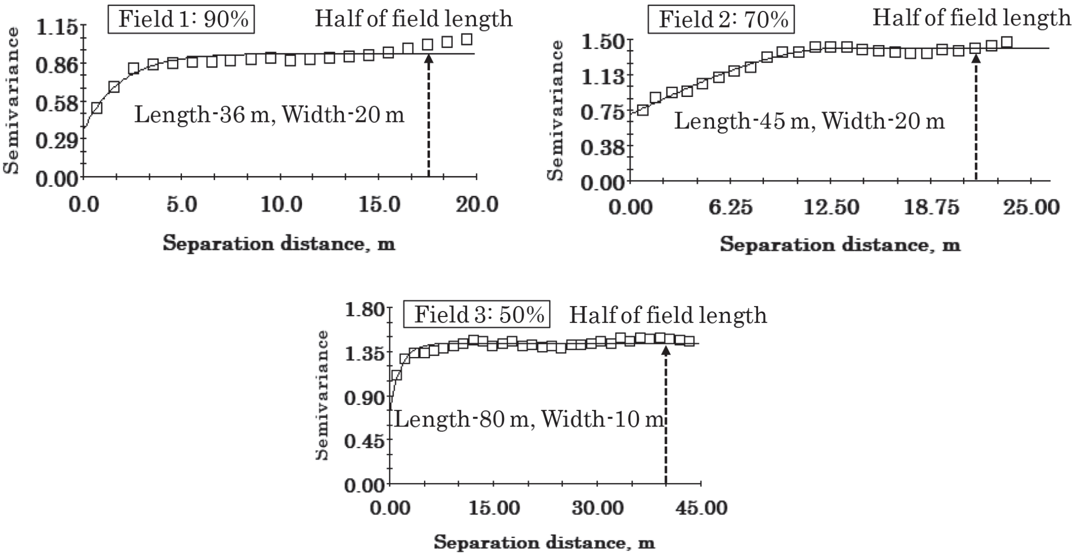

Fig. 6. Semivariograms of three Zoysia grass fields with their best fitted curves and parameters.

model). The optimized range values varied widely, from 5.74 m (exponential model) to 24.49 m (linear model). Similarly, a wide range of optimized parameter values were found in different semivariogram models for the 50% turfgrass growth field. The optimized nugget values varied in different models from 0.65% (linear to sill model) to 1.32% (linear model). A wide range of sill values from 1.42% (linear to sill model) to 1.50% (linear model) and range values from 1.20% (Gaussian model) to 43.30% (linear model) were found for the 50% turfgrass growth field.

In this study, isotropic exponential and spherical models were fitted to the experimental semivariograms. The optimized semivariogram parameter (nugget, sill, and range) values of the fitted semivariogram models are presented in Table 2. The exponential model was found to best fit data for turfgrass the field with 90% growth coverage. The R^2 values ranged from 0.696 (linear model) to 0.843 (exponential model) and the RSS values ranged from 0.039 (exponential model) to 0.679 (linear model). The spherical (SPHR) and linear to sill (LTIS) models were very close, indicating a close performance of the models for the turfgrass field with 70% growth. The performance of the linear to sill (LTIS) model is also

Table 2. Growth level and fertilization level isotropic variogram parameters of three fields

Model*	Field	Nugget (C_0)	Sill (C_0+C)	Range (A0)	Q (C/C_0+C)	R^2	RSS
	90%	0.346	0.933	1.900	0.629	0.843	0.039
EXPN	70%	0.644	1.451	5.740	0.556	0.949	0.053
	50%	0.711	1.435	1.560	0.505	0.780	0.040
	90%	0.407	0.920	4.390	0.558	0.804	0.048
SPHR	70%	0.703	1.407	13.17	0.500	0.968	0.036
	50%	0.714	1.429	3.250	0.500	0.666	0.061
	90%	0.413	0.917	3.080	0.550	0.793	0.051
LITS	70%	0.704	1.409	9.940	0.500	0.965	0.037
	50%	0.654	1.424	1.710	0.541	0.568	0.075
	90%	0.460	0.921	2.060	0.501	0.805	0.049
GAUS	70%	0.710	1.421	6.050	0.500	0.958	0.066
	50%	0.703	1.426	1.200	0.507	0.600	0.071
	90%	0.718	1.034	19.49	0.305	0.696	0.679
LINR	70%	0.965	1.561	24.49	0.381	0.735	2.860
	50%	1.321	1.503	43.30	0.121	0.505	0.086

* EXPN–exponential model, LITS–linear to sill, SPHR–spherical, GAUS–Gaussian, LINR–linear model

acceptable as the R^2 and RSS values were very similar for the 70% growth field with R^2 values ranging from 0.735 (linear model) to 0.968 (spherical model) and RSS values ranging from 0.036 (spherical model) to 2.86 (linear model).

The Kriging interpolated maps of turfgrass growth and fertilizer recommendation showed gradual and non–random spatial variability across the grass field. Fig. 7 shows the grass growth and fertilizer application maps for 90%, 70%, and 50% sod production fields. Five levels of *Zoysia* grass growth status and fertilizer were recommended based on the *Zoysia* grass growth coverage of the experimental fields. These maps illustrate the *Zoysia* grass growth and recommended fertilizer variations within the field. In the field with 90% growth coverage, higher growth was found in the middle area of the field in the range of 8.0 (80%) to 9.0 (90%) growth levels, and some edges of the experimental field showed less growth in the range of 5.0 (50%) to 6.0 (60%) levels. Therefore, lower fertilizer levels in the range of 0.5 (5%) to 1.0 (10%) in the middle area and higher fertilizer level in the range of 3.5 (35%) to 4.7 (47%) in the edges of the field were recommended.

Moderate grass growth variations were found in the 70% growth coverage field; some areas in the middle of the field were found to have higher and moderate grass growth coverage in the range of 8.0 (80%) to 9.0 (90%) levels. Some edges of the field were found to have a grass growth level of less than 5.0 (50%). Hence, a lower fertilizer level in the range of 0.5 (5%) to 1.5 (15%) in the middle area and higher fertilizer level in the range of 3.0 (30%) to 4.0 (40%) in the edges of the field was recommended.

Whereas, high grass growth variations were found in the 50% grass growth coverage field, showing less grass growth in most of the middle area of the field in the range of 4.0 (40%) to 5.0 (50%) and some edges of the field with high growth coverage in the range of 6.0 (60%) to 7.0 (70%) levels. Therefore, fertilizer recommendations also varied over the field, showing a higher

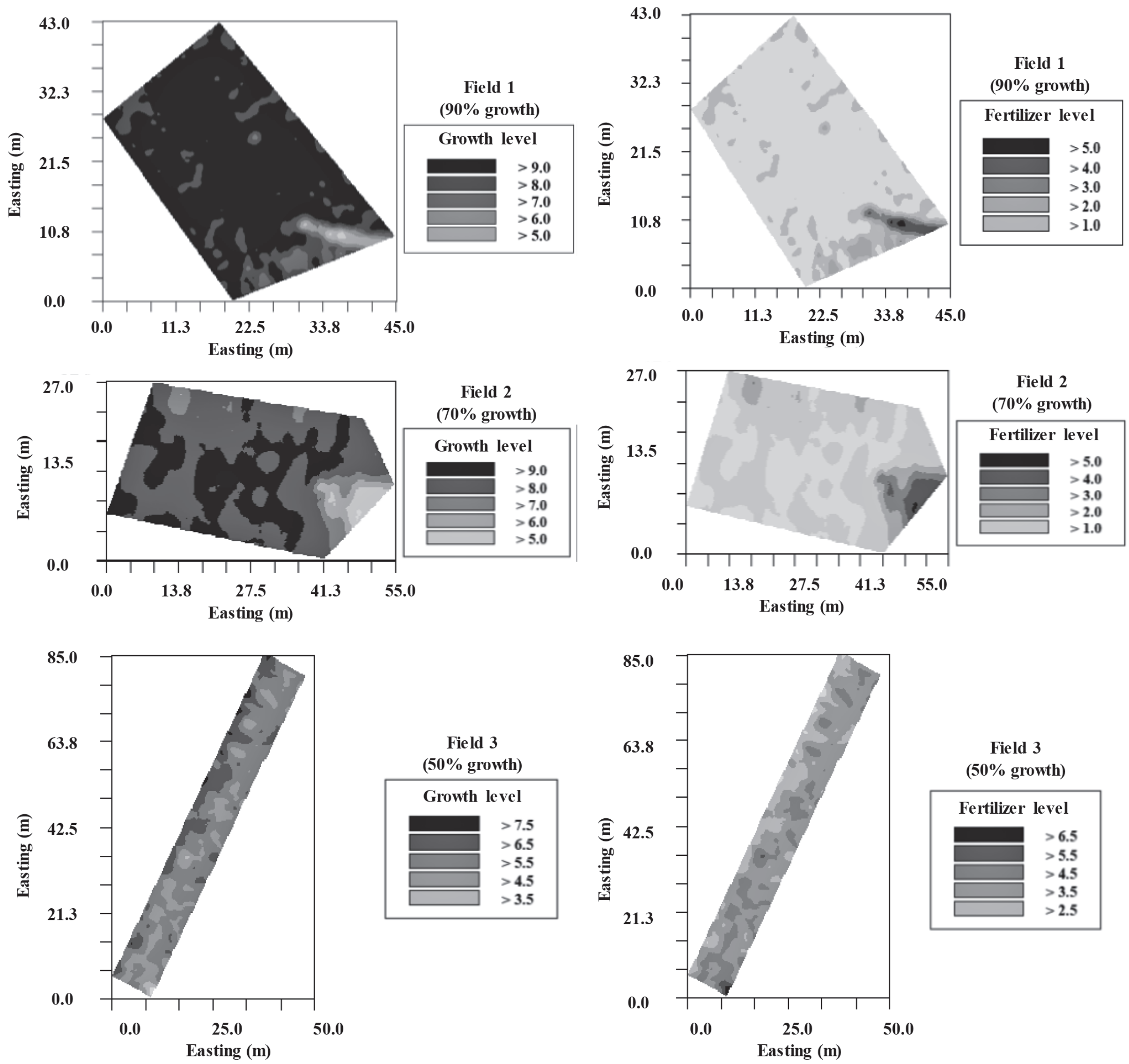

Fig. 7. Grass growth (left) and fertilizer application (right) maps for the fields with grass growth coverage levels of 90%, 70%, and 50%.

fertilizer rate in the range of 2.0 (20%) to 4.0 (40%) levels in the middle part of the field and a fertilizer level of 2.0 (20%) to 3.0 (30%) was recommended in some edges of the field.

Economic benefits of VRF

A uniform fertilizer application rate of 10 (100%) level would require roughly 260 kg N/ha, 280 kg N/ha, and 275 kg N/ha for the 90%, 70%, and 50% grass growth coverage fields. Comparing uniform fertilization to these fields, if the recommended fertilizers were variably applied it could save roughly 23.5%, 16.5%, and 18.5% per hectare for the 90%, 70%, and 50% coverage fields. Although nutritional input varies depending on climate zone, soil type, or species, the general yearly requirements for *Zoysia* grass are recommended at 10 g N/m^2, 19.5 to 29 g N/m^2, and ~34.2 g N/m^2 for lower (i.e., home lawn), medium (i.e., golf course fairway, athletic field), and higher maintenance areas (i.e., higher leaching soil, sod production field), respectively (Carroll *et al*., 1996; Patton *et al*., 2017). According to the reported nutritional recommendation and field map images, nitrogen fertilizer in the *Zoysia* grass sod production field can be applied at a minimum rate of 23 g N/m^2 per year for medium to high growth level areas (i.e., growth levels 6 to 9 for 70% or 90% covered field), while up to 30 ~34.2 g N/m^2 per year for <4 growth level areas such as the 50% covered field.

If this system is applied to a golf course fairway established with Korean lawngrass (*Z. japonica*), where the recommendation rate ranges from 20 to 30 N/m^2 per year, the highest growth level area (>9) with medium soil P and K contents will have a 4:1:2 ratio of N:P_2O_5:K_2O, which equals to 19.5 g N, 4.8 g P_2O_5, and 9.6 g K_2O per square meter per year with the application of about 115 g of a compound fertilizer (16:4:8) (www.aesl.ces.uga.edu). A higher rate will be required for the lower growth level segments <4 or if clippings are removed, where the compound fertilizer will be increased up to 172 g per square meter per year (divided by about 43 g in spring, June, July, and September).

Variable rate fertilization is promising and could save a big amount of fertilizer. But uniform fertilization with an average amount of fertilizer could enhance fertilizer use efficiency. Farmers could take some images from well–grown to less grown areas of a grass field and based on the growth calibration shown in this study, the recommended fertilizer could be set for the entire field for real–time fertilizer application.

CONCLUSIONS

Aiming at variable fertilizer recommendations for sod production fields, an image–based variable rate fertilization system was developed in this study. A CCD camera was mounted on the top front of a mower tractor and *Zoysia* grass images were acquired from three different sod production fields with coverage density of about 90%, 70%, and 50%. Based on the calibration between image processed results (i.e., CIS values) and grass growth levels in our previous research (Kabir *et al*., 2016), *Zoysia* grass growth levels for the three different sod production fields were quantified with position information gathered by GPS.

Linear relationships among the CIS values and zoysia grass growth levels were identified and inverse relationships were derived for variable fertilizer recommendations. The relationships between grass growth levels and fertilizer recommendations exhibited linear relationships for the three different fields. Variations in the growth levels of the *Zoysia* grass were found for the same field; therefore, different levels of fertilization were recommended.

Semi–variance analyses were carried out to characterize the spatial *Zoysia* grass growth distribution. The best semivariogram model was selected comparing the R^2 and RSS values for different lag sizes and lag intervals. The exponential models fit well for the 90% and 50% grass growth coverage field, whereas a spherical model was found to be the best fit for the 50% grass growth coverage field. The Kriging interpolated *Zoysia* grass growth and fertilizer recommendation data were mapped to show gradual and non–random spatial variability for three experimental sod production fields. This variable fertilizer recommendation system with average amounts of fertilizer could enhance fertilizer use efficiency, reflecting grass growth status effectively for sod production and could help operators to achieve efficient variable fertilization.

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AUTHOR CONTRIBUTIONS

Md. Shaha Nur KABIR performed the experiments, analyzed the data, and prepared the draft manuscript. Sun–Ok CHUNG designed and supervised the research. Bo–Eun JANG assisted the experiments and data analysis. Yong–Joo KIM participated in the design and data analysis. Geung–Joo LEE advised grass growth quantification and fertilizer recommendation. Kyeong–Hwan LEE contributed preparation of the equipment and data collection. Takashi OKAYASU and Eiji INOUE advised data analysis and manuscript revision. All authors assisted in editing of the manuscript and approved the final version.

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