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The sensitivity analysis of cultivar parameters for DSSAT CERES-Maize model using long term weather data

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UNDER THE DIRECTION OF PROF. KWANG-SOO KIM

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The sensitivity analysis of cultivar parameters for CERES-Maize model using long-term weather data

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Abstract

The uncertainty of model arise from input data, equation, and parameters. The sensitivity analysis would be used to assess the degree of uncertainty, which would facilitate improvement of a crop model. Little efforts have been made to assess impact of cultivar parameters under a long term climate condition, which would be useful for examining reliability of climate change impact assessment studies using crop models. In this study, we focused on sensitivity analysis of cultivar parameters using 30 years of weather data.

Six cultivar parameters in CERES-maize model were subjected to sensitivity analysis. Weather data observed for 30 years and single soil parameter set at a site in Suwon area used in sensitivity analysis. The total number of simulation was 3.9×10^{8} to accommodate the range of parameters and simulation conditions based on a complete factorial design. Sensitivity of parameters were analyzed in terms of ear weight, biomass, and yield.

It was found that P5, P1, and G3 were influential parameters in ear weight, biomass, and yield, respectively. The error term were mainly derived from climate and unknown error. Particularly, the interaction resulted from climate and planting date made a variation of sensitivity index to influential parameters (P1, P5, and G3). Climate change condition made a sensitivity index of influential parameters to be changed in decadal analysis. For example, in ear weight, the rank of impact of parameters in 1980s was P1 > P5 > G3 but changed in 2000s was P5 > P1 > G3. The result of sensitivity analysis using OAT was similar with that of ANOVA. For example, the rank of OAT was P5 > P1 > G3 > G2 > P2 > PHINT in ear weight.

Our results indicated that cultivar parameters associated with thermal time had greater sensitivity than other parameters in simulation of maize growth and yield. To reduce the uncertainty derived by temperature, it is recommended that the experiment should be performed under ambient temperature conditions to make sure accurate cultivar parameter values in estimation process. The minimum temperature and daily temperature difference would cause change of sensitivity index in decadal analysis on sensitivity index. It would be better using long term weather data to figure out the response of parameters under climate change condition. The result of sensitivity analysis could be differed by experimental conditions; the version of DSSAT, sensitivity analysis method, parameter range, climate data, crop management data, sample size, and soil conditions. Quantifying the impact of simulation conditions for conducting sensitivity analysis would help understand accurate response of parameters.

Keywords: Sensitivity Analysis, Cultivar Parameter, Maize, ANOVA, DSSAT, CERES-Maize, long term weather

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Introduction

Assessment of grain yield using crop models would support policy making in food security as well as daily decision making of crop management (Rosenzweig et al. 2014, Garcia and Fereres 2012). For example, Mueller et al (2012) suggested that yield gap analysis under climate change would help development of water and nutrient management strategy in a region. Dobermann and Cassman (2004) suggested that fertilizer application would be optimized to achieve high nitrogen use efficiency when information for proper decision-making become available at a farm scale.

As interests in decision making based on crop growth simulations have been increased, considerable efforts have been made to improve reliability and robustness of crop models (Glotter et al. 2016, Coucheney et al. 2015). For example, Lizaso et al. (2011) reported that modification of submodules for a crop model would improve accuracy of simulated crop growth. Van Oort et al. (2015) reported that submodules for temperature responses was altered to improve rice growth simulation. Wit et al. (2007) suggested that WOFOST model could be improved by enhanced soil moisture module based on an Ensemble Kalman filter.

Assessment of the uncertainty would help identification of priorities for crop model improvement. Monod et al. (2006) suggested that the uncertainty of a model would result from input data, equation, and parameters. For example, weather data could have errors even when they were obtained at a weather station, which would cause uncertainty in estimates of crop growth. Weather data estimates obtained from spatial or temporal interpolation would increase the uncertainty of yield predicted using a crop model. Equations used in the model represent only a part of crop response under a field condition, which would cause additional uncertainties in predicting crop yield. The size

of data used for determination of parameter values could affect the uncertainty of a given model (Briggs et al. 2012).

In crop growth simulations, a large number of parameters are commonly used to represent a complex system in a cropland (He et al. 2010). For example, the CERES-maize model requires at least 25 parameters to specify characteristics of soil. Those parameters used in submodules often causes large uncertainty on model outputs (Graeff et al. 2012). Assessment of uncertainty for a given set of parameters would be useful to identify submodules on which improvement should be focused.

The sensitivity analysis would be useful to assess the degree of uncertainty, which would help improve the reliability of a crop model (Helton et al. 2005). For example, Varella et al. (2012) performed the sensitivity analysis of the STICS model to represent the impact of parameters associated with soil on yield and nitrogen absorption. Chan et al. (1997) assessed the impact of parameters and interactions between parameters using sensitivity analysis. The outcome of sensitivity analysis could be used to determine which parameters should be simplified or which properties of the crop should be measured more accurately (Wallach et al. 2006).

Sensitivity analysis to improve crop growth simulations has been focused on parameters used in a crop model (Lamboni et al. 2009). For example, Makowski et al. (2006) performed a sensitivity analysis on the 13 cultivar parameters to quantify impact of grain quality and yield. Vanuytrecht et al. (2014) suggested guidlines for model simplification assessing the impact of cultivar and soil parameters. Zhao et al. (2014) analyzed sensitivity and uncertainty of parameters for cultivar, environment, and management in simulation of yield, biomass, flowering date, and maturity date.

It would be useful to identify a suitable method that provides robust outcomes for given computing resources (Frey and patil. 2002). Local sensitivity analysis can provide

simple response of parameters with relatively low computational costs (Cariboni et al. 2007). For example, Bert et al. (2007) investigated the impact of cultivar parameters to grain yield using a local sensitivity analysis method. Although global sensitivity analysis requires high computational resources, it would be useful to investigate both main and interaction effects. The choice of sensitivity analysis approach could be determined on the number of parameters of interest. For example, Confalonieri et al. (2010) evaluated six types of sensitivity analysis methods under 11 parameters to understand computationally efficient approaches.

The outcome of sensitivity analysis on parameters could be affected by the duration of crop growth simulation (Qin et al. 2013). Thus, it would be preferable to perform sensitivity analysis using a long term climate data. For example, Wang et al. (2005) conducted sensitivity analysis on parameters of the EPIC model using 34 years of weather data. Brooks et al. (2013) used 30 years of weather data to perform sensitivity analysis on simple equations for yield and water balance. It would be also possible to examine uncertainty of parameters under climate change conditions when long term weather data are used for sensitivity analysis.

Little efforts have been made to assess uncertainty of cultivar parameters under climate change conditions, which would be useful to characterize uncertainty in determining crop phenology as well as crop yield. The objective of this study was to perform sensitivity analysis of cultivar parameters using 30-years of weather data. We focused on analysis of main and interaction effect of parameters on uncertainty of crop model, detailed analysis of error term in the sensitivity analysis, and climate change impact of parameters under climate conditions.

Materials and Methods

1. *CERES-Maize*

The CERES-Maize model, which is a part of the DSSAT, has been used to simulate growth of maize. The CERES-Maize model has been used for impact of climate change and yield prediction for precision farming and crop management (Jones et al. 2003; Thorp et al. 2008; Royce et al. 2001). The CERES-Maize model consists of submodules to simulate phenology, growth, and yield for a given cultivar (Porter et al. 2010; Jones et al. 2010).

Six parameters are used to simulate maize growth for a cultivar of interest in the CERES-Maize model (Table. 1). These parameters are used to characterize the response of crop in terms of growth, yield, and phenology under a given environmental condition. Those parameters can be classified into two groups associated with phenology (P1, P2, P5, PHINT) and yield (G2, G3), respectively. P1 and P5 are directly related with the response of cultivar to GDD. P2 is the value that represents the response of cultivar to sunshine duration. PHINT determine the interval for which leaf would appear under given GDD. The value of G2 indicate a potential kernel number for a given cultivar. G3 is used to determine filling of each kernel at a given time.

2. *Input data for simulations*

Crop growth simulations were performed for 30-years at a study site. Because of long term data availability, Suwon, Korea (126°989´E, 37°270´N) was chosen as the site of interest. Weather data including daily maximum and minimum temperature, solar radiation, and precipitation were collected from 1981 to 2010. Those data were obtained from an internet based weather database (http://metsky.kma.go.kr) operated by Korea

Meteorological Administration (KMA).

Soil input data were obtained from soil analysis results performed at the site (Table 2). Soil layers were divided into 8 layers from 5cm to 150cm. The value of CEC was investigated near surface of soil (~30cm).

Planting dates were set for a period of 13 weeks, which were from Julian date of 87 - 171. The values of parameter for crop management was determined under the assumption of a standard cultural practices (Son et al. 2013). For example, planting density was set to be 66,000 ha-1. The fertilizer application rate for nitrogen, phosphorus, and potassium were assumed to be 174kg ha-1, 30kg ha-1, 69kg ha-1, respectively, which is recommended by Rural Development Administration, Korea. Maize growth simulation was performed under rain-fed condition, which is common in the region.

3. Determine parameter range and DOE

The values of parameters were gathered from all of sample parameter files available from the DSSAT model. The range of parameter values for senstivity analysis were derived from those values (Table 3). The complete factorial design, which examine all of combinations for given parameters, was used to consider all the variations of each parameters for sensitivity analysis. The use of complete factorial design allows through examination of interaction effects between parameters. The number of experiment is defined as the number of factors and its levels, which are denoted by n and p, respectively. The total number of experiment is determined as p^n (Ginot et al. 2006). We consider all the variation in the number of 10^6 experiments. Because simulations were performed for each combination of parameters during the period of 30 years for 13 planting dates, the total number of simulation amounted to 3.9×10^8.

4. *Sensitivity analysis of cultivar parameters*

Biomass, ear weight, and yield were subjected to sensitivity analysis of cultivar parameters using analysis of variance (ANOVA). In the ANOVA, the effect of each parameter and their interactions on model outputs were analyzed. The domain of each parameter was defined using the range of corresponding parameter values listed in the cultivar parameter file (MZCER045.CUL) of the DSSAT version 4.5.

4-1. Sensitivity Index

The variance V of model output (Y) for the given set of cultivar parameters is determined as follow (Chan et al. 1997):

$$\mathrm{V(Y)} = \sum_{\alpha} V_{\alpha} + \sum_{\alpha<\beta} V_{\alpha\beta} + \cdots + V_{\alpha\beta\cdots\omega} \tag{1}$$

Where V_{α} indicates variance of simulation results over the range of the parameter α collapsed over levels of other parameters. $V_{\alpha\beta}$ represents the variance of results over parameter between α and β. The sensitivity corresponding to α can be measured using the ratio of Va and V(Y) as follows:

$$S_{\alpha} = \frac{V_{\alpha}}{V(Y)} \tag{2}$$

Where S_a is the main effect sensitivity index. To take into account the effect of interactions between α and β, sensitivity indices for the second order effects can be calculated as follows:

$$S_{\alpha\beta} = \frac{V_{\alpha\beta}}{V(Y)} \tag{3}$$

Sensitivity indices for higher order effects can also be calculated in a similar way. Total sensitivity index (ST_{α}) for a given parameter α is determined as the sum of all the

sensitivity indices for main and interaction effects as follows:

$$ST_{\alpha} = S_{\alpha} + \sum_{\alpha<\beta} S_{\alpha\beta} + \cdots S_{\alpha\beta\cdots\omega} \tag{4}$$

4-2. Six-way repeated measures ANOVA

Total sensitivity index is obtained using ANOVA analysis. Six-way repeated measures ANOVA was performed to examine main, interaction, and error effect resulted from parameters, weather, and planting dates. In the ANOVA analysis, 2-way interactions were used.

The result obtained for each parameters could be describe as below:

$$Y_{ijklmn} = \mu + a_i + b_j + c_k + d_l + e_m + f_n + \frac{1}{2!}\sum_{\substack{i,j \\ (i\neq j)}} X_i \cdot X_j + e_{ijklmn} \tag{5}$$

Where Y_{ijklmn} is estimates of crop growth for a given set of parameters. μ is the overall mean of results, $a_i + b_j + c_k + d_l + e_m + f_n$ is the number of factors and each level's effect. $\frac{1}{2!}\sum_{\substack{i,j=1 \\ (i\neq j)}} X_i * X_j$ means second order interactions between parameters. e_{ijklmn} is an error that comes from unknown effect and non-considered effect.

Each parameter such as a, b, c, d, e has its level of 10; $a = \{a_1, a_2, \cdots, a_{10}\}$, b = $\{b_1, b_2, \cdots, b_{10}\}$, c = $\{c_1, c_2, \cdots, c_{10}\}$, d = $\{d_1, d_2, \cdots, d_{10}\}$, e = $\{e_1, e_2, \cdots, e_{10}\}$, f = $\{f_1, f_2, \cdots, f_{10}\}$. The levels of each parameter such as i, j, k, l, m, n describe the value from parameters in the level of 10. For example, a_i can be calculated as $a_i = (\bar{y}_{i\ldots\ldots} - \bar{y}_{\ldots\ldots})$. $\bar{y}_{i\ldots\ldots}(i = 1, 2, \ldots 10)$ is average of parameter α related to level of i and $\bar{y}_{\ldots\ldots}$ is total average of all components. In case of repeated measures ANOVA, $\bar{y}_{i\ldots\ldots}$ can be defined as $\sum_j \ldots \sum_o y_{jklmno}$ and $\bar{y}_{\ldots\ldots}$ can be defined as $\sum_i \ldots \sum_n \sum_o y_{ijklmno}$.

In this equation, $\sum_o$ means the repetition integrated between planting date and weather. It can be divided into $\sum_o \sum_p y_{ijklmnop}$, which shows effect of planting date and weather separately.

Second order interactions is denoted by multiplication between parameters such as $a_1 * b_1$. To represent all combinations, each of parameters and its levels need to be converted into matrix or array. Let $\mathrm{X} \in \{\mathrm{a}, \mathrm{b}, \mathrm{c}, \mathrm{d}, \mathrm{e}, \mathrm{f}\}$ as a matrix. X_i and X_j can be defined as i and j th factor of X. multiplication X_i and X_j is now meaning that all combinations between two parameters are considered. All of interactions are required to be integrated, however, duplicated combinations are still exist such as $X_1 * X_2$ and $X_2 * X_1$. To remove this duplicated combinations, sum of all interactions should be divided by 2!. The second order interactions can be obtained as below:

$$\frac{1}{2!} \sum_{\substack{i,j \\ (i \neq j)}} X_i * X_j \tag{6}$$

Let μ move to the left side of equation (6) and square both sides to obtain sum of square, following equation can be obtained:

$$\sum_i \cdots \sum_o (Y_{ijklmno} - \mu)^2 \sum_i {a_i}^2 + \cdots + \sum_n {f_n}^2 + \sum \left(\frac{1}{2!} \sum_{\substack{i,j \\ (i \neq j)}} X_i \cdot X_j \right)^2 + \sum_i \cdots \sum_o e_{ijklmno} \tag{7}$$

Where $\sum_i \cdots \sum_o (Y_{ijklmno} - \mu)^2$ is Total sum of square (SST), $\sum_i {a_i}^2$ is sum of square of a (SS_a), $\sum_n {f_n}^2$ is sum of square of f (SS_f), $\sum \left(\frac{1}{2!} \sum_{\substack{i,j \\ (i \neq j)}} X_i \cdot X_j \right)^2$ is sum of square for 2 variables ($SS_{X_i \cdot X_j}$). $\sum_i \cdots \sum_o e_{ijklmno}$ is sum of square for error (SSE).

The equation (7) can be simplified as belows:

$$\text{SST} = SS_a + SS_b + SS_c + SS_d + SS_e + SS_f + SS_{X_p \cdot X_q} + \text{SSE} \quad (8)$$

Where SST is total variation at model reaction, SS_a is main effect of a, SS_b is main effect of b, SS_f is main effect of f, $SS_{X_p \cdot X_q}$ is interaction between two factors $SS_{X_p \cdot X_q \cdot X_r}$ is interaction among three factors.

ANOVA based sensitivity index could be determined with equation (2) as belows:

$$S_a = \frac{V_a}{V(Y)} = \frac{SS_a}{SST} \quad (9)$$

$$S_{X_p \cdot X_q} = \frac{V_{X_p \cdot X_q}}{V(Y)} = \frac{SS_{X_p \cdot X_q}}{SST} \quad (10)$$

The sensitivity analysis is implemented based on ANOVA with six parameters using PROC ANOVA procedure function in SAS. Due to limitation in computing power, sensitivity analysis was performed up to the second order interaction. Replications such as climate and planting date were analyzed as errors to understand how much they interact with cultivar parameters and their impact to sensitivity analysis.

5. *analysis of error term*

The residual obtained from ANOVA analysis for main and interaction effects were referred to an error term. In repeated measures ANOVA, the error is derived from the number of iteration for ANOVA and interactions between independent variables. Measured errors are quantified by a method to get sensitivity index such as $\frac{SSE}{V(Y)}$ and confirm the impact of them to an error.

5-1. Errors from repetition

Errors resulted from replication of simulations for 30 years weather data and 13 planting date would be considerably large compared with other errors (Verma 2016). The effects

of the climate and management on simulation outputs can be classified as an error in the simulation because it is not considered as cultivar parameter but replication of ANOVA analysis. To quantify impact of error including climate variability and planting date, the sensitivity analysis to each parameter has been analyzed with each year and each planting date.

Climate variability was analyzed in two steps. At first, sensitivity index of climate was analyzed by each year. Then, sensitivity index under climate change conditions was analyzed averaging the values of sensitivity index for 10 year periods, e.g., 1981-1990, 1991-2000, and 2001-2010.

The impact of planting dates to sensitivity index of cultivar was analyzed using a planting date as a reference date. It was assumed that Julian date of 129 would be a common date for planting. Senstivity analysis results using simulation outputs from on 129 were used as a reference outcome of the analysis. Outputs from other planting dates were compared with those from reference date.

6. *OAT(one-at-a-time) analysis*

In addition, OAT and ANOVA methods were compared if these two methods would have similar results although requirements for computing resources was considerably lower for the former that the latter. OAT analysis method is simple and useful tool to understand trend of sensitivity of result (Pogson et al. 2012). It would help to interpret ‘changing trend’ to the parameter in terms of long term weather condition and various planting date. The analysis of OAT have been implemented through average all the values of same levels including repetitions. For example, the results of ear weight obtained by second level of P5 are averaged regardless of its repetition.

Results

1. OAT

The response of cultivar parameters had positive influence on all variables except for P1 and PHINT (Fig 1). P1 had a strong non-linear response compared with other parameters. In case of ear weight and yield, the response of P1 turned positive into negative at the level 8. The impact of PHINT was relatively lower than that of other parameters. PHINT had a monotonically decreasing trend for all the variables.

Differences between slope of regression analysis for ear weight, bio mass, and yield were observed respectively. P5 had the greates slope (5.96, 397.9) whereas PHINT had the smallest slope (0.5,18.9) for ear weight and yield, respectively. For biomass, the slope was greatest (96.4) and smallest (12.1) for P1 and G2, respectively.

2. *Main effect*

The sensitivity of parameters differed by biomass, ear weight, and yield (Fig. 2). For example, the parameter of GDD until juvenile stage (P1) had sensitivity index values of 0.17, 0.54, and 0.11 in simulations of ear weight, biomass, and yield, respectively. Parameters that had greater sensitivity to a set of variables associated with yield did not necessarily had greater sensitivity to other sets of variables.

The parameters associated with growing degree days (GDD) for development stages were identified as a dominant factor in the sensitivity analysis. For example, the parameter of GDD during grain filling stage (P5) was the most sensitive in the simulation of ear weight and yield. In the simulation of biomass, GDD until juvenile stage (P1) was the most sensitive parameter. On the other hand, the parameters of sunshine duration, kernel number, and phyllochron interval had relatively low sensitivity to biomass, ear weight, and yield.

3. *Interactions*

Sensitivity index for higher order effects was not necessarily lower than that of the lower order effects (Fig 3). For example, sensitivity index of yield in biomass was 0.0009 whereas that of interaction between G2 and G3 (G2*G3) was 0.0119 in simulations of biomass. The impact of P5*G3 (0.0029), which ranked as 8th was larger than the impact of PHINT.

Overall, interaction effect associated with P1 and G3 tended to have greater sensitivity index than that with other parameters for variables of interest. For example, sensitivity index for interaction between P1 and other parameters, e.g., P1*PHINT, P1*P2, and P1*P5, was greater than that for other interactions except for G2*G3 in simulation of biomass. The sensitivity index of G2*G3 was similar to that of P1*PHINIT for biomass and yield.

4. *Errors*

Sensitivity index for error was relatively high compared with that of main effect (Fig. 1). For example, the index value of error effect was equivalent to about 181%, 50%, and 121% of that for most influential main effect in simulations of ear weight, biomass, and yield, respectively. Most of the errors were contributed to the effect of climate and undefined error (Fig. 4). For example, sensitivity index of error associated with climate accounted for 68%, 76%, and 59% of ear weight, biomass, and yield, respectively. Interactions between climate effect and parameters were also the major contributor to sensitivity index of error in the simulation of ear weight, biomass, and yield.

The large variation was observed for influential parameters (P1, P5, G3) on each variables (Fig. 5a). For example, the variation of P1 was considerably larger than that of

other parameters. The sensitivity index of P1 was determined by a season ranged from 0.06 to 0.44 during 30 years of simulation. P2, G2, and PHINT tended to have less variation under weather conditions for 30 years. Except for P1, most of the parameters tended to had low variation in simulation of biomass compared with yield and ear weight.

Sensitivity of parameter was relativley small for a range of planting dates compared with a long term climate conditions (Table 4). The most sensitive parameter for a given planting date was P5 in simulation of ear weight and yield of which sensitivity index was 0.03 and 0.05, respectively. In simulation of biomass, P1 was the most sensitive parameter by changes in planting dates. The large variation for 13 planting dates was also obtained for P1, P5, and PHINT (Fig. 5b).

5. Decadal analysis of sensitivity

The change of sensitivity index for P1, P5, and G3 was identical under climate change condition except for biomass (Fig. 6). Sensitivity of P1 had a decreasing trend in all the variables, i.e., ear weight, biomass, and yield whereas that of P5 and G3 tended to increase overtime. The differences in sensitivity index ranged from 0.01 to 0.05 between 2000s and 1980s. In simulation of ear weight, for example, the impact of P1 and P5 in 1980s was similar. In 19990s, however, the impact of P5 was greater than that of P1.

Discussion

Climate change condition made the impact of influential cultivar parameters (P1, P5, G3) to be changed in the sensitivity analysis. For example, the impact of P1 in ear weight has been changed about 5% between 1980s and 2000s. Delicate field experiment design would be recommended to estimate parameter values under high temperature condition, because the climate change condition made the sensitivity index of P5 and G3 to be changed. Change of rank for P1 and P5 was observed under climate change condition in ear weight. Thus, using long term weather data on sensitivity analysis would be recommended to understand accurate response of cultivar parameters.

Main reason of change of sensitivity index in ear weight and yield would be resulted by minimum temperature, daily temperature difference, and radiation (Fig.S1). As increase of minimum temperature in potential P1 period (April to July) would supply the enough GDD during juvenile stage, the sensitivity of P1 decrease from 1980s to 2000s in ear weight, biomass, and yield. The reason why increase of sensitivity index of P5 and G3 in ear weight and yield was daily temperature differences that cause nutrient partitioning to vegetative growth rather than kernel filling (Donald and Hamel 2012). As the impact of P5 and G3 to biomass was small, the change of sensitivity index in biomass under climate change conditions was small too. Solar radiation would also affect to simulation output under climate change condition. In this study, as we selected a single site, the trend of solar radiation are not representative. The impact to ear weight, biomass, and yield by the change of radiation in different area need to be analyzed in further study.

Sensitivity analysis using long term weather data would show other aspect of result that short term weather data can't make. In this present study, the change of sensitivity index for ear weight and yield was dependent on the change of climate. Sensitivity analysis using short term data would not represent impact of parameters. Sensitivity analysis under

long term weather would be required to investigate accurate response of parameter, particularly in ear weight and yield.

Although the slope of regression analysis of OAT was not the same as the value of sensitivity index derived from ANOVA, the result of OAT and ANOVA showed a same rank in ear weight, biomass, and yield, respectively. The result of OAT showed that ANOVA couldn't detect in sensitivity analysis. For example, the impact of PHINT was negatively sensitive in OAT but ANOVA showed just a positive sensitivity. Non-linearity have been observed in OAT in ear weight, biomass, and yield, respectively. P1 and G3 have non-linearity curve in the OAT analysis. We can understand both response curve of parameter at a given conditions and quantified impact of parameters through OAT analysis and ANOVA analysis.

Our results indicate that cultivar parameters associated with thermal time had greater sensitivity than other parameters in simulation of maize growth and yield. The sensitivity index for parameters such as P5and P1 was greater than those for other parameters to plant growth and yield. For example, P5 and P1 were always ranked as the influencing parameters for all variables. Having an effort into P5 and P1 would help to improve preciseness of outputs in terms of ear weight, biomass, and yield.

Interactions between weather*parameter contributed to large proportion of error resulted in sensitivity analysis. In the present study, although half of the error term comes from single effect of weather but interactions also accounted for large proportion. For example, interactions were took into account 0.26, 0.21, 0.20 of error term for ear weight, biomass, and yield. Variations of sensitivity index was mainly resulted from Weather*parameter interactions. This suggest that sensitivity index of cultivar parameter would be affected by weather conditions. To obtain reliable values of parameters, it is recommended that the experiment would be performed to multiple years to minimize

impact of weather conditions.

Although the impact of P1 was large on ear weight and yield, the variation of P1 derived by planting date was not variable that we didn't expected. It means that P1 mainly determined biomass and indirectly affect to ear weight. The variation of P5 is connected with P1 on ear weight and yield because start point of P5 was determined by P1 in terms of GDD. For example, if P1 have a low value that make the plant early flowering, the start point of P5 come earlier. At that period, P5 need enough temperature to produce grain but weather can't provide enough temperature in early start of P5. These conditions made a variation of P5 in ear weight and yield derived by planting date.

Planting date may have a role as a thresh hold to determine ear weight, biomass, and yield. P1, P5, PHINT had a one-sided trend in variation of sensitivity index by planting date. It means that the variation would be reduced when the model meet the specific planting date to produce ear weight, biomass, and yield. The range of planting date as a repetition need to be corrected to eliminate unexplainable points.

Crop growth and yield are generally determined by biological processes depending on temperature. As such, In the CERES-Maize, specific growth habits for a given cultivar are simulated based on the parameters associated with GDD, e.g., P1 and P5. The temperature, which is used to calculate GDD, affect not only to the growth but also to the stress. For example, high temperature to maize was documented to have a negative impact to the growth, reproductive organs, and phenology (Cheikh and Jones 1994, Cicchino et al. 2010). If the stress factors that related to temperature are applied to the model in a form of parameter, the more precise results could be predicted in terms of biomass and yield.

Degenring et al. (2004) suggested that a simplification process for non-influential parameters of a model could be implemented. For example, P2 and PHINT were the

parameters that could be applied to simplification process because they were ranked as less influencing parameters for most of variables. Dejonge et al. (2012) reported that PHINT would be one of sensitive parameter in crop growth simulation. However, our results indicated that PHINT would be one of non-influential parameter. The difference between two studies would result from the experimental conditions. For example, the range of parameters and sample size as well as analysis methods would result in such a difference (Wang et al. 2013, Confalonieri et al. 2010, Iman and Conover. 1980). It would be helpful to simplification process with identifying the impact of PHINT using diverse methodologies.

The computational intensity could be increased as exponentially when the sensitivity analysis is performed with lots of parameters using ANOVA. The computational intensity is dependent on the number of parameters and its levels. Especially, the level of parameter is the factor that determine computational intensity. Sensitivity analysis based on ANOVA would not be adequate in case of lots of parameters and its levels. Iooss and Lemaître (2015) suggested that methodology of sensitivity analysis could be determined by preciseness of results (screening, variance decomposition), computational cost, and model complexity with regularity. In further sensitivity study, Considering computing performances, model complexity, and the number of parameters and its levels are required to conduct sensitivity analysis with reasonable costs and precise results.

It is considered that the parameters that still not be identified to its impacts would be used to DSSAT model. For example, about 30 soil parameters are applied into the simulation of DSSAT, however, quantified influence of soil parameters is not documented yet because of computational intensity. To quantify impact of parameters with moderate computational cost, extended Fourier Amplitude Sensitivity Test (eFAST) method has been generally used (Marino et al. 2008,). eFAST method is well known to be useful where lots of parameters are being considered (Varella et al. 2010). The

sensitivity analysis to soil parameters based on eFAST would help quantify the impact of parameters, which can be used for model simplification process.

TABLES AND FIGURE

Table 1. Description of cultivar specific parameter used in CERES-Maize model

Name	Description
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8) during which the plant is not responsive to changes in photoperiod.
P2	Extent to which development proceeds at a maximum rate (which is considered to be 12.5 hours).
P5	Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8).
G2	Maximum possible number of kernels per plant.
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day).
PHINT	Phyllochron interval : the interval in thermal time (degree days) between successive leaf tip appearances.

Table 2. Soil parameter values obtained from Suwon region

Items / Depth	Soil Texture	Soil color	SLRO [a]	SLDR [b]	SLNF [c]	SRGF [d]	SLLL [e]	SDUL [f]	SSAT [g]	CEC [h]	SLHW [i]	SLOC [j]	SLNI [k]
5						1	0.11	0.227	0.450	17.8	6.6	1.53	0.13
15						1	0.11	0.227	0.450	17.8	6.6	1.53	0.13
30	silt					0.638	0.103	0.201	0.451	16.3	6.3	1.06	0.09
45	loam	black	70	0.5	1	0.472	0.099	0.193	0.452	N/A [l]	6.3	0.97	0.10
60						0.35	0.099	0.193	0.452	N/A [l]	6.3	0.97	0.10
90						0.223	0.088	0.173	0.450	N/A [l]	6.3	0.72	0.07
120						0.122	0.079	0.165	0.452	N/A [l]	6.3	0.43	0.04
150						0.067	0.086	0.178	0.450	N/A [l]	6.3	0.2	0.02

[a] SLRO = runoff curve number , [b] SLDR = drainage rate, [c] SLNF = mineralization factor, [d] SRGF = root growth factor, [e] SLLL = lower limit ($cm^3\ cm^{-3}$), [f] SDUL = upper limit ($cm^3\ cm^{-3}$), [g] SSAT = saturated ($cm^3\ cm^{-3}$), [h] CEC = cation exchange capacity ($Cmol\ kg^{-1}$), [i] SLHW = pH in water, [j] SLOC = total organic carbon (%), [k] SLNI = total nitrogen (%), [l] N/A = Not Available

Table 3. Given cultivar parameter range used in DSSAT and the value of cultivar parameters used in the sensitivity analysis

Name	Parameter values									
	1	2	3	4	5	6	7	8	9	10
P1	5.0	55.3	105.6	156.0	206.3	256.6	307.0	357.3	407.6	458.0
P2	0.0	0.2	0.4	0.6	0.8	1.1	1.3	1.5	1.7	2.0
P5	429.0	496.3	563.6	631.0	698.3	765.6	833.0	900.3	967.6	1035.0
G2	380.0	467.7	555.5	643.3	731.1	818.8	906.6	994.4	1082.2	1170.0
G3	4.4	5.7	7.09	8.4	9.7	11.1	12.4	13.8	15.1	16.5
PHINT	38.9	42.9	46.9	50.9	54.9	58.9	62.9	66.9	70.9	75.0

Table 4. Change of sensitivity index compared with integrated Planting date and single planting date (DOY 129)

Parameter	△Sensitivity index		
	ear weight	biomass	yield
P1	0.00771	-0.01218	-0.00052
P2	-0.00099	-0.00248	-0.00129
P5	-0.03184	-0.00751	-0.04686
G2	-0.00208	-0.00002	-0.00333
G3	-0.01250	-0.00120	-0.01821
PHINT	0.00101	-0.00029	0.00050

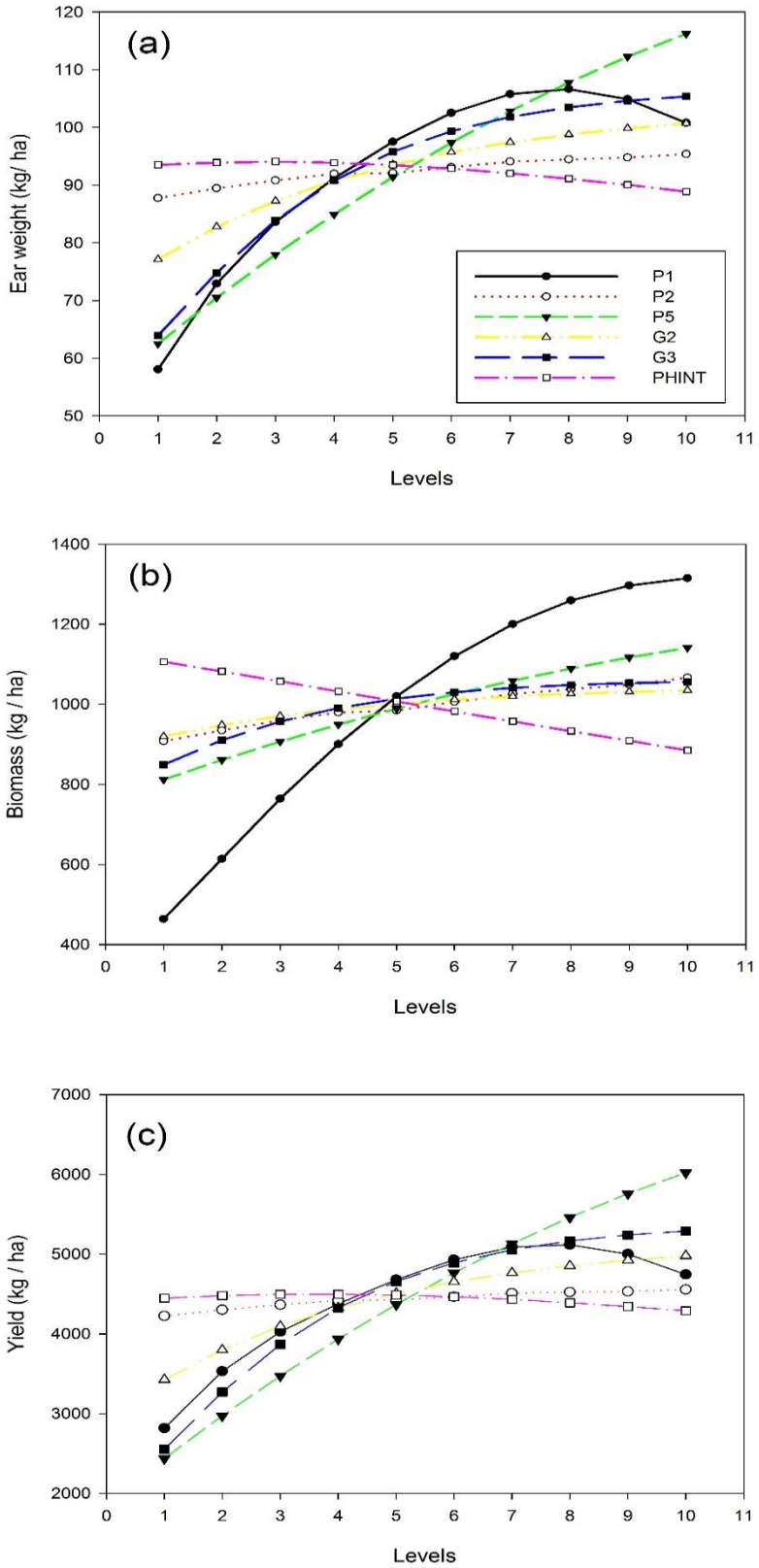

Figure 1. The result of OAT averaged at each level (a) response curve of parameters in ear weight (b) biomass (c) yield

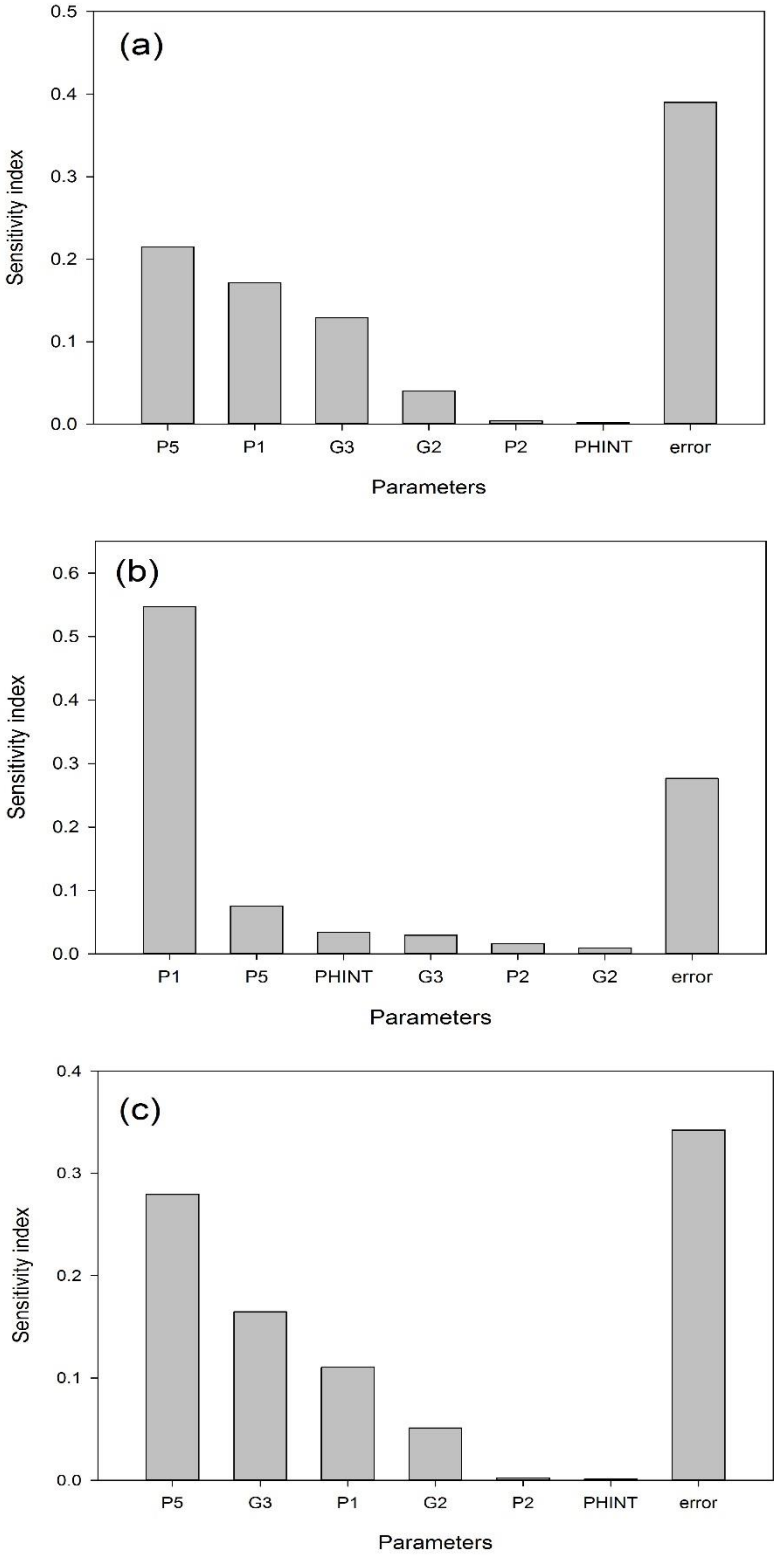

Figure 2. The result of sensitivity analysis for main effects (a) ear weight (b) biomass (c) yield

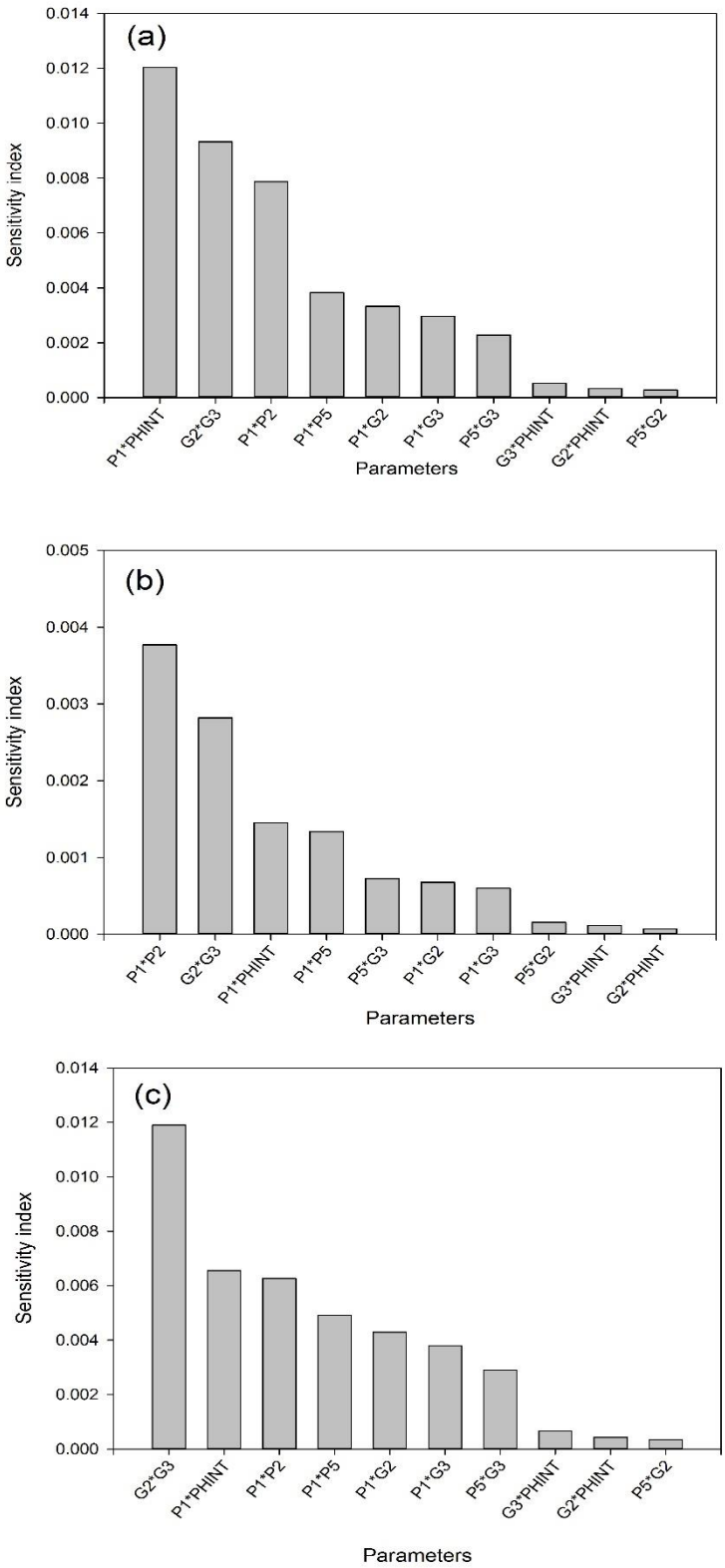

Figure 3. The result of sensitivity index for interaction effects

(a) ear weight (b) biomass (c) yield

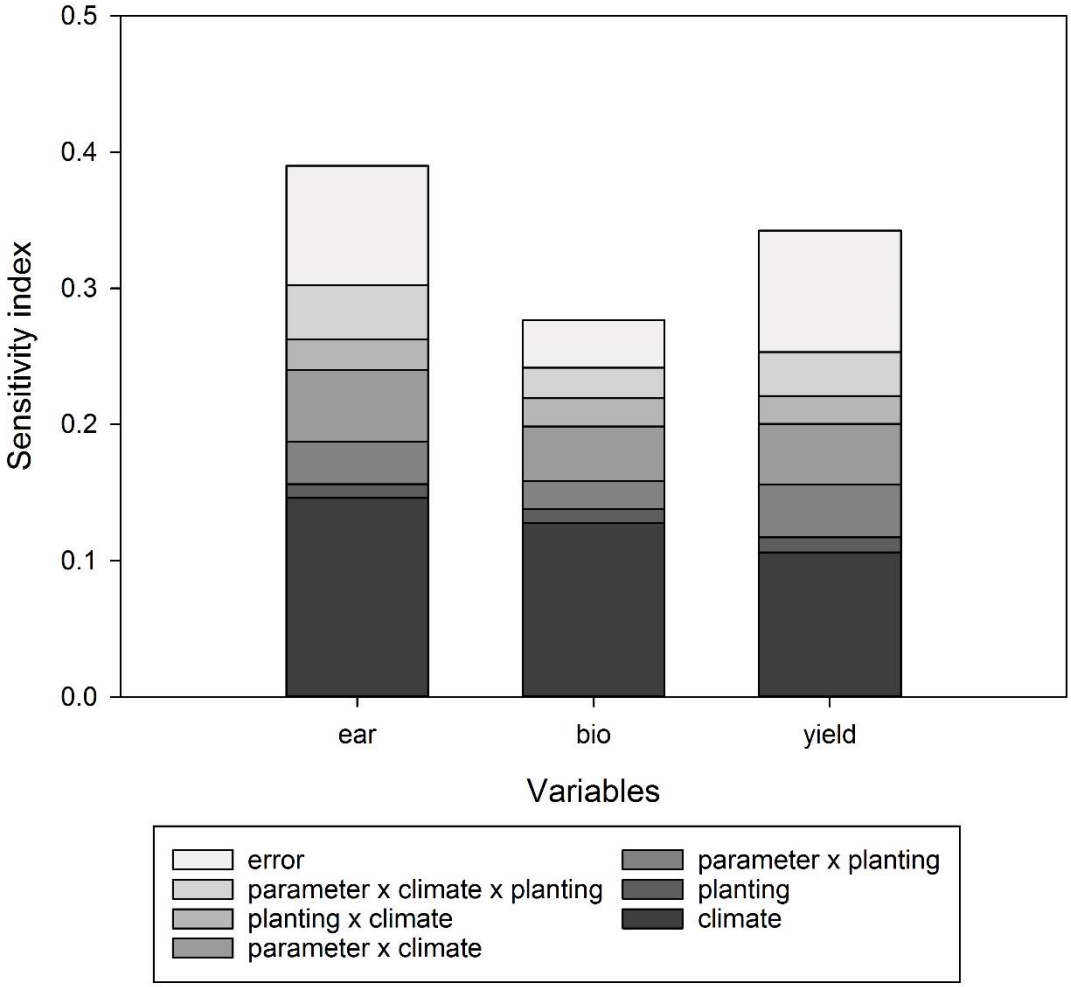

Figure 4. Main cause of error in sensitivity analysis using ANOVA on ear weight, biomass, and yield

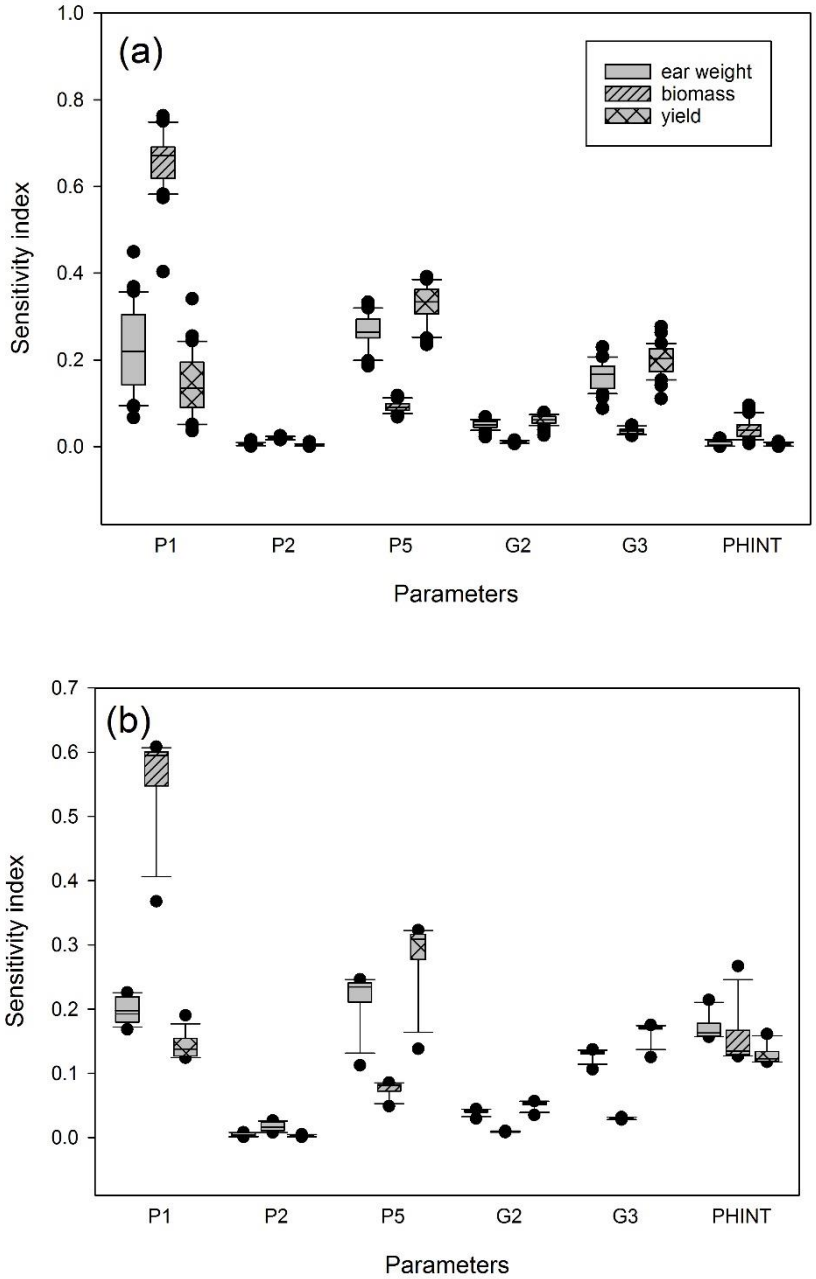

Figure 5. Variability sensitivity index derived by repetition (a) variation of sensitivity index by climate (b) variation of sensitivity index by planting date

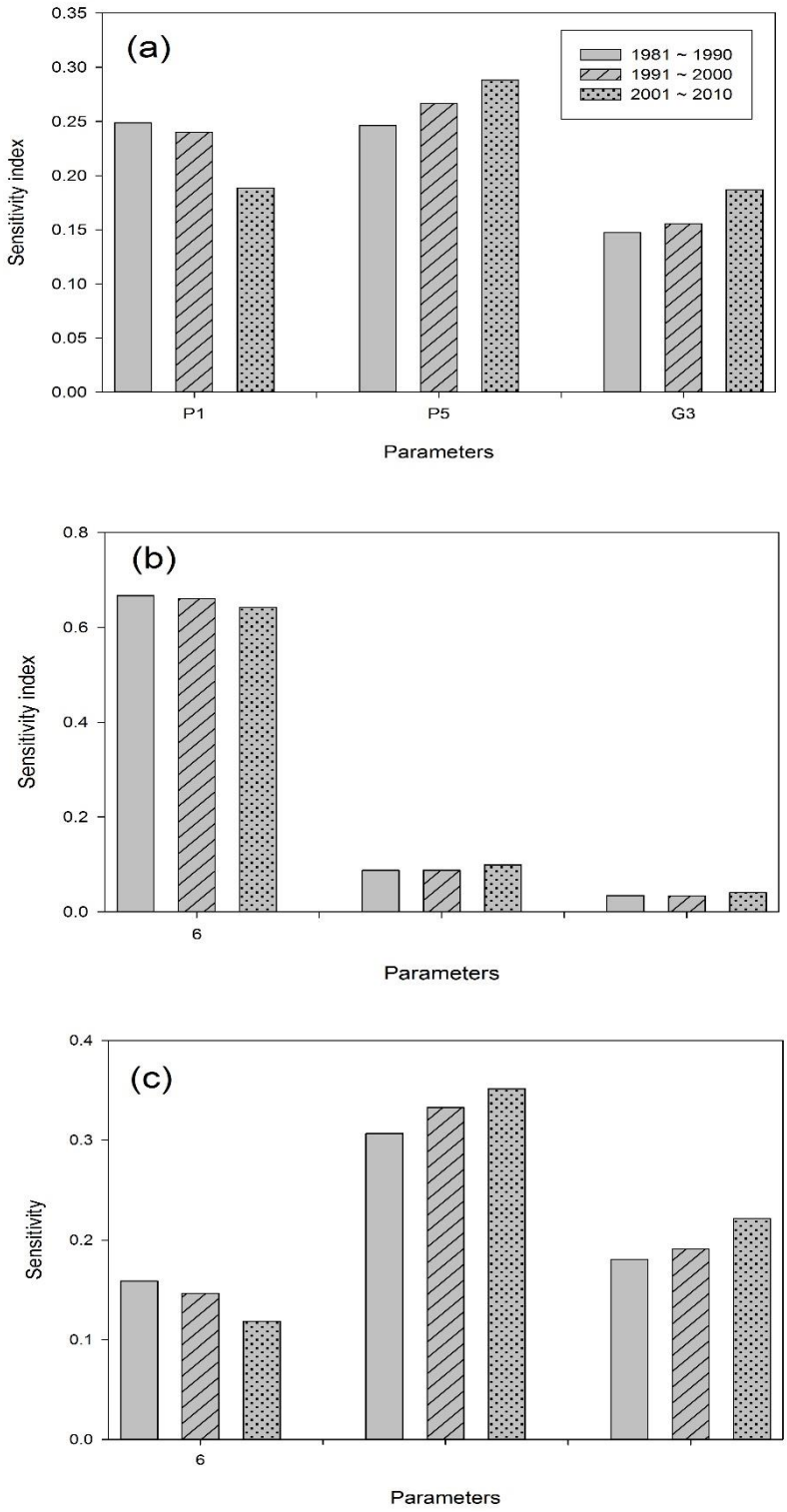

Figure 6. Decadal change of sensitivity index resulted by climate change

a) ear weight (b) biomass (c) yield

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APPENDIX

Weather data analysis

Weather data analysis has been implemented using 10 years average of weather variables such as maximum temperature, minimum temperature, and solar radiation. In potential growing season (April ~ October) in Suwon area (Fig5.a~5.c). Later P5 period (September and October) showed increase trend under climate change condition in maximum temperature and minimum temperature. The gap between 2000s and 1980s in maximum temperature was about 1.2℃ and 0.9℃ at September and October respectively. In case of minimum temperature, the gap was about 2.2℃ and 2.12℃ in September and October, respectively. Most of potential period for P1 (April ~ July) also showed increase trend except for July.

The distribution of solar radiation in 1980s, 1990s, and 2000s have similar formation during most of season. The solar radiation gradually increased, changing of analysis term. Peak point of radiation was 16.38 W/m^2, 17.82 W/m^2, and 19.07 W/m^2 in 10 year average radiation of May for 1980s, 1990s, and 2000s, respectively. Radiation decrease in July and August has been observed in all 1980s, 1990s, and 2000s. Main reason of decrease trend for solar radiation in July and August is the rainy season in the Korea.

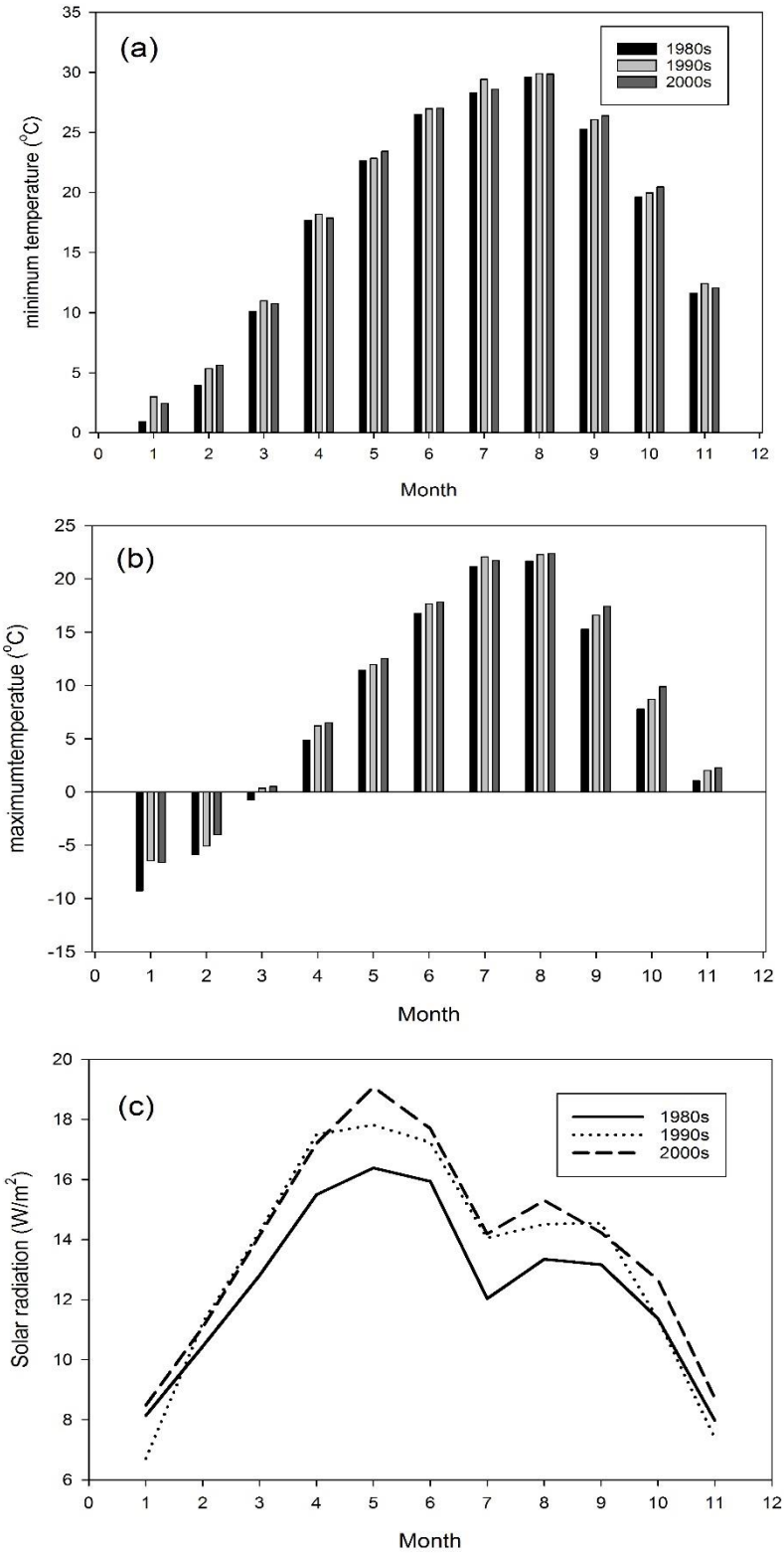

Fig. S1. Weather data analysis categorized by 10 year averaged monthly data (a) maximum temperature (b) minimum temperature (c) solar radiation

국문초록

작물모델의 신뢰성과 정확성을 확보하려는 노력에도 불구하고, 불확실성은 입력자료, 수식, 그리고 모수에 의해서 발생하게 된다. 민감도 분석은 불확실성의 정도를 평가하는데 유용할 수 있으며, 작물모델의 신뢰성을 개선시키는데 도움을 줄 수 있다. 최근 연구에서는 장기간의 기상조건에서 품종 모수 자체에 대한 연구가 미미하다. 게다가, 결과의 정확도 높다고 알려진 ANOVA 를 이용하는 민감도 분석은 거의 없었다. 이번 연구에서는, 30 년간의 기상자료를 사용하여 품종 모수의 민감도 분석을 수행하는데 목적을 두었다. CERES-maize 모델에서 사용하는 6 개의 품종 모수를 대상으로 하여 민감도 분석을 수행하였다. 수원 지역의 30 년 관측 기상자료와 단일 토양 모수를 이용해 분석을 수행하였다. 비료 시용량은 질소, 인, 칼륨 순으로 각각 174kg ha^{-1}, 30 kg ha^{-1}, 69 kg ha^{-1} 를 처리하였다. 완전요인설계를 통해 총 3.9 x 10^8 개의 모수 조합을 고려하여 품종 모수와 기상에 따른 이삭중, 생체중, 종실중의 반응을 확인하였다.

P5, P1, 그리고 G3 가 이삭중, 생체중, 종실중에 대해서 영향력있는 모수로 분석이 되었다. ANOVA 분석중에 발생하는 오류는 ANOVA 분석의 반복에 의해 발생하였으며 주로 기상과 밝혀지지 않은 오류가 대부분이었다. 특히, 모수와 기상간의 상호작용이 주요한 모수들(P1, P5, G3)의 민감도 지수를 변화시키는데 큰 영향을 주고 있었다. 주요 모수의 민감도 지수는 기후변화조건에서 각각 다르게 나타났다. 1980 년대에는 영향력이 P1 > P5 > G3 순이었다면 2000 년대 들어서는 P5 > P1 > G3 순으로 바뀌었다.

기후변화에 의한 민감도 지수의 변화는 최저기온과 일교차의 변화에 의해 발생하였다. OAT 방법을 이용한 민감도 분석 결과와 ANOVA 분석의 결과가 유사하게 나타났다.

이러한 결과는 적산온도와 관련이 있는 품종 모수들이 다른 품종 모수들에 비해서 옥수수의 생육과 수량성에 큰 민감도 지수를 가지는 것을 나타냈다. 품종 모수 추론단계에서 기상에 의해 발생하는 불확실성을 줄이기 위해서, 다년간의 실험을 통해 기상 조건의 영향력을 최소화 하는 실험이 요구된다. 민감도 분석의 결과는 DSSAT 모델의 버전, 민감도 분석 방법, 모수의 범위, 기상자료, 재배관리자료, 표본 수, 그리고 토양 조건과 같은 실험 조건에 의해 달라 질 수 있다. 영향력있는 모수들의 민감도 지수가 기상에 의해 변화하였기 때문에, 장기간의 기상자료를 이용한 민감도 분석이 정확한 결과를 얻는데 도움이 될 것이다.