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THE ROLE OF WATER STRESS IN CREATING SPATIAL YIELD VARIABILITY IN SOYBEANS

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Introduction

Recent advancements in yield monitors and global positioning systems that can create spatial yield maps have generated much excitement and controversy among farmers and researchers. Site-specific field management promises to maximize field level net return and minimize environmental impact by managing fields using spatially variable management practices. The success of site-specific field management depends upon discovery of relationships between environment, management, and resulting yield variability, and ultimately, how these relationships can be exploited to compute optimum prescriptions. Farmers are faced with trying to determine how to manage variability to improve profits. Researchers are trying to develop methods to analyze causes of yield variability, and determine how to develop prescriptions for fertility, and cultural practices to capitalize on variability across field. While environmental, management, soil, and pest factors have been studied for many years, researchers are just beginning to determine how these factors vary across fields, contributing to spatial yield variability.

Several studies have focused on establishing spatial relationships between crop yields and soil and site characteristics. Cambardella et al. (1996) used two multiple linear regression procedures to analyze the effect of soil properties on crop yield variability within a 16 ha field. They found that aggregate size distribution contributed significantly to yield variability in seven out of the seven years. Bulk density, soil moisture, and soil texture contributed significantly to yield variability in four out of the seven years. Sudduth et al. (1996) found that soybean yield response curves generated by two methods, pursuit projection regression and neural network analysis, agreed well with measured yields. Ambuel et al. (1994) developed a fuzzy logic model to relate soil characteristics to describe yield variability within two 16-ha fields in Central Iowa.

Soil moisture related stress (drought or excess water) can cause significant variability due to variations in soil moisture holding characteristics, rooting depth and distribution, and drainage patterns across a field. This can be deduced through several studies which have shown good correlation between yield and elevation, yield and soil type, and yield and position on the landscape (Khakural et al, 1996; Jones et al., 1989).

Interactions between soil moisture content, water table depth, and root depth and distribution play a role in determining the extent of water stress, especially late in the season when seed filling dominates root growth in terms of sink demand. In Iowa, many fields in the Clarion-Nicollette-Webster soil group are tile drained, which creates spatially variable water table depths (James and
Fenton, 1993), which can limit rooting depth, across fields. This scenario leads to the following hypothesis for these tile drained fields: high soil moisture content limits rooting depth, leading to spatially variable water stress late in the season as soil moisture contents are reduced due to drainage, root water uptake, and limited rainfall.

One complexity in analyzing yield variability is the lack of methods that can incorporate varying levels of stresses over the season to evaluate the effects of interactive stress on growth, development, and yield. It is difficult to account for temporal interactions of stress on growth using traditional statistical analysis. For instance, while some success has been achieved to show relationships between soil type or elevation with yield variability by regression approaches, these approaches do not directly account for the dynamic interaction of soil moisture availability, root water uptake, and water related stresses that can occur and affect plant growth each day during the season. Understanding the temporal interaction between stresses and plant growth processes is imperative to understanding and quantifying yield variability. Methods to accurately compute interactions of stress on growth will ultimately lead to the ability to determine optimum prescriptions.

Process oriented crop growth models can be used to study temporal and spatial crop response to stress (Batchelor, 1996; Allen et al., 1996). Crop models offer several advantages over traditional statistical methods to evaluate growth and yield response to environment and management:

1. They can be used as a tool to explore hypotheses related to yield variability.
2. When inputs are properly characterized, they can integrate the effects of dynamic and multiple stress interactions with crop growth processes, and subsequently, yield.
3. After being validated for a field, these models can be used to develop and evaluate prescriptions including factors such as optimum variety selection, fertilizer and irrigation application rates, plant populations, planting date, and row spacing.
4. They allow analysis of what-if scenarios and assist in the identification of appropriate prescriptions.
5. They can be used to assess economic and environmental impact of prescriptions.

The CROPGRO-Soybean (Hoogenboom et al., 1994) and CERES-Maize (Jones and Kiniry, 1986) crop models were developed to compute growth, development, and yield on homogeneous units (either plot, field, or regional scale), and have been demonstrated to adequately simulate crop growth at a field or research plot scale. These models require inputs including management practices (variety, row spacing, plant population, fertilizer and irrigation application dates and amounts) and environmental conditions (soil type, daily maximum and minimum temperature, rainfall and solar radiation). From this information, daily growth of vegetative, reproductive, and root components are computed as a function of daily photosynthesis, growth stage, and water and nitrogen stress. A soil moisture and nitrogen balance model are used to compute water and nitrate levels in the soil as a function of rainfall and soil moisture holding properties.

Process-oriented crop growth models are a promising tool to help researchers search for relationships between environment, management, and yield variability. The objective of this study was to demonstrate the use a soybean crop growth model to test the hypothesis that water stress creates significant yield variability in a soybean field in Iowa.

**Procedures**

**Hypothesis**

We hypothesize that wet spring weather leads to high soil moisture content in Clarion-Nicollette-Webster tile drained fields in Iowa. High soil moisture leads to higher water tables, which are
typically seen under these conditions. High water tables restrict maximum rooting depth. In addition to this, upward water redistribution due to perching of the water table may cause oxygen depletion in saturated layers with existing roots, which may impede root growth and cause root senescence. This leads to spatial variability in maximum rooting depth. During grain fill, rainfall usually diminishes, and shallow roots lead to water stress during the critical grain filling period. Variability in rooting depth and soil moisture availability in the root zone leads to variable water stress, which results in yield variability.

We are proposing to use the CROPGRO-Soybean (Hoogenboom et al., 1994) model to test this hypothesis. The model computes a complete water balance based on daily rainfall (Figure 1). Water is redistributed through the soil based on principles outlined in Kiniry and Jones (1986) for the CERES-Maize model. The soil is divided into approximately 10 layers, and the user specifies the lower limit, drained upper limit, saturated moisture holding capacity, saturated hydraulic conductivity, and proportion of layer that is mined by roots (root weighting factor) for each layer. Downward flow of water is computed based on the amount the water content in a layer exceeds the drained upper limit, and how much water the next layer can hold. Maximum water movement from a layer is limited by either a drainage coefficient (fraction of water than can be drained from a layer in a day under free drainage conditions) or saturated hydraulic conductivity. Perched water tables can be created by setting the saturated hydraulic conductivity ($K_{sat}$) in a deep soil layer in the profile (usually 150-180 cm depth) to a small value. This reduces water outflow from the bottom of the profile, and causes water to perch upward in the profile during rainfall events. Using this technique, wet spring conditions can fill up the profile, creating shallow water tables of 50-100 cm depths.

Figure 1. Diagram showing the different processes that affect water availability, depth to water table and root development

In the model, daily increase in root depth is a function of soil temperature and soil moisture. A maximum increase in rooting depth per day is computed, and reduced under cool temperatures. In addition to this, when the soil moisture content approaches the saturated moisture holding capacity, oxygen depletion reduces root growth into a layer. This approach allows a water table (defined by a saturated layer) to limit rooting depth. A maximum root depth can be specified for a soil, which limits rooting depth due to physical constraints in the soil or physiological constraints of the plant. Currently, the model does not reduce leaf expansion, photosynthetic rate, or senesce roots under oxygen depleted conditions.

One unknown factor is the distribution of roots in the soil profile. A root distribution factor is used in the model to define the fraction of water and nutrients in a soil layer that can be mined by roots in each soil layer. Thus, a factor of 1.0 in a layer indicates that roots in that layer can mine 100% of
available water and nutrients, while a factor of 0.1 indicates only 10% can be mined. Root water uptake in a soil layer is a function of available water, root length volume, and root distribution factor in the soil layer. In this research, we assume a triangular root distribution shown in Figure 1. Roots are distributed evenly in the top 30 cm, and propagation of roots decreased linearly with respect to depth from 30 cm to the bottom of the root zone. The bottom of the root zone is limited by either a user selected depth, water table depth, or carbon limitations.

Water stress is computed each day in the model by dividing potential water uptake by evapotranspiration demand. This results in a factor ranging from 0 under total water stress, to 1.0 under no water stress conditions. This factor is then used to directly reduce daily photosynthesis, and to modify certain water stress sensitive developmental stages. In the model, water stress can also increases carbon partitioning to roots, thereby increasing rooting depth to search for more water. The implementation of water stress effects on photosynthesis is the key to implementation of the above outlined hypothesis in the model.

Site Description
Spatial yield distribution of soybean (*Glycine max.* [L.] Merr) was investigated in a 16 ha field in Boone County, IA. The field used a conventional farming method consisting of a corn (*Zea mays* L.) - soybean rotation, conventional tillage, and application of commercial fertilizer and pesticides. The field, which is the southwest (SW) quadrant of the Baker farm, was discussed in Colvin et al. (1995). Figure 2 shows the arrangement of the eight transects on the field. Each transect consists of 28 soybean yield plots or grids. This gave a total of 224 grids with measured yields. Each grid was 12 m by 46 m in length. Final soybean yield was measured from the 5 center rows in each grid using a plot combine and weigh wagon for 1992, 1994, and 1996. Yield from each strip was used to represent yield in the larger grid. For the modeling analysis, data from grids with missing yield, or measured yield of 0 kg/ha were eliminated. Thus, 213 of the 224 available grids were included in the analysis.

Figure 2. A map of the harvest plots for the Baker farm southwest field showing the eight transects

Soil Properties
The soils within the field are predominantly from the Clarion-Nicollet-Webster soil association that occupies the majority of the Des Moines Lobe glaciated region in Iowa. The site is typical of low-relief swell and swale topography characteristic of broad areas of the Des Moines lobe surface.
A detailed soil map of the field (Steinwand, 1992) was obtained from the National Soil Tilth Laboratory (NSTL) in Ames, IA. Nine major soil classes were identified and distributed across the field (Table 1). These soil types are commonly found on the Des Moines Lobe, and estimates of soil physical properties were provided by Logsdon (1995 unpublished) of the NSTL. Thus, estimates were available for lower limit, drained upper limit, saturated moisture content, saturated hydraulic conductivity, bulk density, and organic carbon at several depths for each soil type. Properties for the predominant soil type in each grid was used to represent soil properties in each grid.

Table 1. Soil series, classification, and drainage class for detailed soil map units identified at the Baker farm southwest field

<table>
<thead>
<tr>
<th>Soil Series</th>
<th>Taxonomic Classification</th>
<th>Drainage Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Okoboji tax.</td>
<td>Fine-loamy Cumulic Haplaquoll</td>
<td>VPD</td>
</tr>
<tr>
<td>Terril</td>
<td>Fine-loamy Cumulic Hapludoll</td>
<td>MWD</td>
</tr>
<tr>
<td>Nicollet</td>
<td>Fine-loamy Aquic Hapludoll</td>
<td>SWP</td>
</tr>
<tr>
<td>Storden</td>
<td>Fine-loamy (calcareous) Typic Udorthent</td>
<td>WD</td>
</tr>
<tr>
<td>Harps tax.</td>
<td>Fine-loamy Cumulic Calciaquoll</td>
<td>PD</td>
</tr>
<tr>
<td>Webster</td>
<td>Fine-loamy Typic Haplaquoll</td>
<td>PD</td>
</tr>
<tr>
<td>Clarion</td>
<td>Fine-loamy Typic Hapludoll</td>
<td>WD</td>
</tr>
<tr>
<td>Canisteo tax.</td>
<td>Fine-loamy (calcareous) Cumulic Haplaquoll</td>
<td>PD</td>
</tr>
<tr>
<td>Zenor</td>
<td>Coarse-loamy Typic Hapludoll</td>
<td>SED</td>
</tr>
</tbody>
</table>

a All except Okoboji tax. were in the mixed, mesic family; Okoboji is in the montmorillonitic family.

b VPD, very poorly drained; PD, poorly drained; SWP, somewhat poorly drained; MWD, moderately well drained; WD, well drained; SED, somewhat excessively drained.


Crop Growth Model

Three soil parameters can be adjusted in the model to set up and test this hypothesis. These parameters primarily affect water table depth and rooting depth progress. In this study, we used the saturated hydraulic conductivity ($K_{sat}$) of the bottom layer of the soil profile (180-200 cm) to create perched water tables. High values of $K_{sat}$ in a grid create better drainage conditions resulting in lower water tables. Low values reduce drainage out the bottom of the profile and create higher water tables, which can restrict rooting depth. The second parameter is the soil drainage rate coefficient (SLDR), which represents the number of days required for a soil layer to fully drain down to the drained upper limit. Drainage through a soil layer is limited by either $K_{sat}$ or SLDR, whichever gives the slowest rate. SLDR can be used to create a slow draining soil, which mimics the effects of tile drainage in a grid. High values represent more freely drained soils. Low values can reduce rate of rooting depth increases by creating soil layers that remain above the drained upper limit for longer periods of time. The third soil parameter is the maximum rooting depth, which limits the depth of soil, and subsequently, total water available for uptake. In all grids, we assume a triangular function to estimate the root growth factor (fraction of water that can be mined by roots in a layer) for each grid as a function of maximum rooting depth. In the top 30 cm, it is assumed that roots can mine 100% of the water and nutrients available. From 30 cm down to the maximum rooting depth, this fraction is computed assuming a linear decreasing fraction.
The crop model was linked to a multi-dimensional minimization program to solve for the optimum set of combinations of these three soil parameters for each of the 224 grids in the 16 ha Baker field required to set up and test this hypothesis. The downhill simplex method (Nelder and Mead, 1965), an algorithm that determines the minimum of a function of more than one independent variable, was used in this study. The generic source code (AMOEBA) of the optimization algorithm was taken from the Numerical Recipes handbook (Press et al., 1992).

Three combinations of changes to these three soil parameters were used to test the hypothesis. These scenarios (Table 2) represented changing three different combinations of model inputs (which were not measured) to create the conditions required to test the hypothesis. Parameters were optimized in each of the 224 grids to minimize the root mean square error (RMSE) between predicted and measured yield for 1992, 1994, and 1996.

In Case 1 (Table 2), water tables were established by using low values of SLDR, which reduced drainage. Rooting depth was used to create limitations in total soil volume and soil moisture that can be mined by roots. In Case 2, only rooting depth was adjusted in each grid. The SLDR was set to 0.2 in each layer. In Case 3, we adjusted both K_{sat} of the bottom layer and rooting depth were adjusted. Spatial variability in drainage and water table depths were created by adjusting K_{sat} of the bottom layer. In combination with setting the maximum rooting depth (which can be modified by water table depth), this created a condition that limited rooting depth and imposed water stress during seed filling.

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
<th>SLDR</th>
<th>Rooting depth, cm</th>
<th>K_{sat} in bottom layer, cm/hr</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Optimized SLDR and rooting depth</td>
<td>Optimized</td>
<td>Optimized</td>
<td>Measured</td>
</tr>
<tr>
<td>2</td>
<td>Optimized rooting depth</td>
<td>Measured</td>
<td>Optimized</td>
<td>Measured</td>
</tr>
<tr>
<td>3</td>
<td>Optimized rooting depth and K_{sat} in bottom layer</td>
<td>Measured</td>
<td>Optimized</td>
<td>Optimized</td>
</tr>
</tbody>
</table>

Results and Discussion

Whole Field Soybean Yield

Following the procedures outlined above, soil and root parameters were optimized for each case and for each grid over 3 years to minimize the RMSE between predicted and measured yields in each grid. The first test of the hypothesis was to compare field level predicted and measured yields. The sum of the predicted yield in each grid was close to the measured field level yields for each year. The average field level predicted yield over all 3 years was close to the average 3 year measured field yield of 3098 kg/ha (Table 3). The predicted soybean yield for each of the three cases (3042, 2978 and 2959 kg/ha) compared favorably with the three-year average measured soybean yield for Baker farm (3098 kg/ha). This indicates that the model, in all cases, performed well in predicting field level yields based on summing predicted yields for each grid. Predicted and measured whole field yields showed that the model slightly under predicted whole field yields in 1992 by approximately 10%, while giving good estimates of whole fields in 1994 and 1996 (within 3% of measured yield) (Table 4). In other studies, we have noticed a tendency for the model to under predict yields in 1992. This is likely due to the model not responding properly to the very cool temperatures which occurred during 1992 (Sexton et al., 1997).
Table 3. Summary of error between predicted and measured three-year average field level yields for each case. The three-year average measured yield was 3098 kg/ha.

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
<th>Predicted Yield (kg/ha)</th>
<th>S.D.</th>
<th>RMSE (kg/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Optimized Drainage Rate (SLDR) and Rooting Depth</td>
<td>3042</td>
<td>511</td>
<td>392</td>
</tr>
<tr>
<td>2</td>
<td>Optimized Rooting Depth</td>
<td>2978</td>
<td>539</td>
<td>464</td>
</tr>
<tr>
<td>3</td>
<td>Optimized Rooting Depth and Bottom Layer Ks (Saturated Hydraulic Conductivity)</td>
<td>2959</td>
<td>536</td>
<td>487</td>
</tr>
</tbody>
</table>

*Predicted yield represents three-year field average.*

Table 4. Field level measured and predicted yield for each soybean production year and each optimization scenario.

<table>
<thead>
<tr>
<th>Production Year</th>
<th>Measured Yield (kg/ha)</th>
<th>Predicted Yield (kg/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Case 1</td>
<td>Case 2</td>
</tr>
<tr>
<td>1992</td>
<td>3076</td>
<td>2888</td>
</tr>
<tr>
<td>1994</td>
<td>3119</td>
<td>3075</td>
</tr>
<tr>
<td>1996</td>
<td>3099</td>
<td>3169</td>
</tr>
</tbody>
</table>

**Grid Level Soybean Yields**

The RMSE between predicted and measured yields in each grid over 3 years (Table 3) for case 1 (392 kg/ha) was lower than cases 2 (464 kg/ha) and 3 (487 kg/ha). This indicates that case 1 gave better predictions of yield in the 213 individual grids than case 2 and case 3. In fact, the RMSE of case 1 represents approximately 12% of the field level measured yield for each year. This further indicates that changing SLDR and rooting depth better mimicked soil-water-plant relationships compared to case 2 and case 3 for this version of the model. Figure 3 shows predicted versus measured yields for each grid over 3 years for case 1. Overall, the model gave good results with respect to describing yield variability as a function of spatially variable water stress. Variable levels of water stress were computed by the model across the field, which created spatially variable yields across the field. It is interesting to note that there were several data points with high predicted yields, but low measured yields. In testing this hypothesis, we had no information other than estimates of soil properties and measured yield. Low measured yields could have resulted from other factors such as low plant population, effect of pest and diseases that were not considered in the analysis.

**Error Distribution**

In the next analysis, grids with low measured yields were eliminated because low yields were likely caused from factors not related to water stress (ie. low populations, disease, or weed pressure). This resulted in 207 grids with yields greater than 1000 kg/ha. Overall, the error in predicted yields in these 207 grids were better for case 1, than for case 2 or 3 (Table 5). Case 1 has lower RMSE and higher R² (0.69) values than cases 2 and 3. These results indicate that characterizing drainage rate and rooting depth (and consequently, root growth factors) across the 16 ha field likely mimicks soil moisture dynamics, and accounts for much of the variability in soybean yield for the three production years analyzed in this study. Approximately 69% of the variability in yield could be accounted for by the water stress hypothesis tested with the crop model (Figure 4).
Using the optimized set of drainage rate and rooting depth values for case 1, the model predicted soybean yield within ±10% of the measured yield for 84% of the grids and within ±20% of the measured yield for 92% of the grids (Table 6). The large number of grids with highly variable yields falling within ±10% or ±20% of measured yield indicates ability of the model to describe spatial and temporal stresses and reinforces our approach of using the crop model in predicting yield variability on a sub-field level.

Table 5. Summary of results for 3 optimization scenarios using soybean data without poor-yielding grids. Total number of grids was 207.

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
<th>Predicted Yielda (kg/ha)</th>
<th>RMSE (kg/ha)</th>
<th>R-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Optimized Drainage Rate (SLDR) and Rooting Depth</td>
<td>3076</td>
<td>286</td>
<td>0.69</td>
</tr>
<tr>
<td>2</td>
<td>Optimized Rooting Depth</td>
<td>3007</td>
<td>392</td>
<td>0.51</td>
</tr>
<tr>
<td>3</td>
<td>Optimized Rooting Depth and Bottom Layer Ksat</td>
<td>2989</td>
<td>399</td>
<td>0.50</td>
</tr>
</tbody>
</table>

aPredicted yield represents three-year field average.

Figure 3. Predicted vs measured soybean yield for optimization case 1. Total number of grids: 213.
Figure 4. Predicted versus measured yield for optimization scenario 1 excluding low yielding grids. Total number of grids was 207.

\[
y = 0.7801x + 647.95 \\
R^2 = 0.69
\]

Table 6. Number and percentage of grids falling within a specific yield prediction error range for the three soybean production years.

<table>
<thead>
<tr>
<th>Error Range</th>
<th>Number of Grids in Range</th>
<th>Percentage$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>±5%</td>
<td>386</td>
<td>61</td>
</tr>
<tr>
<td>±10%</td>
<td>533</td>
<td>84</td>
</tr>
<tr>
<td>±20%</td>
<td>584</td>
<td>92</td>
</tr>
<tr>
<td>±30%</td>
<td>610</td>
<td>96</td>
</tr>
</tbody>
</table>

$^a$ Total number of data points is 636. (213 grids x 3 years).

Yield Trend Along Transects

In general, there was good agreement in the trend of predicted and measured yields along different transects in the field. Figures 5a and 5b show an example of the predicted and measured yield trends along two of the transects which had the largest difference between the lowest and highest measured yields. Generally, the model followed the measured yield trend very well in all transects over all years. There are areas along some transects, especially transect 7 (Figure 5b), where there were larger differences between measured and predicted yield. However, the model captured the trend of high and low yields along the transect, which is reflected in the low RMSE values presented in Table 3.
Predicting the correct yield trend is likely more important than predicting the absolute yields along a transect if the model is to be used to develop and evaluate prescriptions. In determining the economic consequences of prescriptions such as optimal plant population or variety for each grid, the analysis should focus on determining the yield response in a grid resulting from different prescription. The difference in net return for two prescriptions can be determined by evaluating the cost of each prescription and the value resulting from the yield response between the prescriptions. Thus, as long as the model responds in a realistic way to changes in prescriptions, the resulting net return between two prescriptions should be realistic.

Figure 5. Comparison of soybean yield along transects (a) number 1 and (b) number 7 for 1996 production year.

Summary and Conclusions
This work demonstrates the value of using a process oriented crop growth model to test hypotheses related to causes of spatial yield variability of soybeans. The hypothesis that water stress creates yield variability within a soybean field was examined. Using this approach, the crop model computed daily carbon and water balances in the plants and soil, and subsequently reduced growth due to spatially variable water stress, resulting in predictions of spatial yield variability. In the best case, water stress explained approximately 69% of the variability in soybean yield over 3 years in 224 grids within a 16 ha field in Iowa. Predicted field level soybean yields compared favorably with the
three-year average measured soybean yield for Baker farm, as well as with the measured yields each year.

Overall, the model gave good predictions in the trend in yields along each of 8 transects in the field. There were instances where the model showed poor agreement between predicted and measured yield on several grids, notably those in low lying areas along transect 7. A possible explanation is the inability of the model to account for run-on or surface or sub-surface flow to a grid coming from several neighboring grids. Another possible explanation is the non-inclusion in the modeling analysis of above ground factors, i.e. plant population, pests and diseases, that may have an effect on yield reduction. Nonetheless, this study has shown that the crop growth model can be used to predict yield variability with reasonable accuracy on a sub-field level.

Finally, the strength of this work is that it characterizes yield variability using a process oriented crop growth model. This is superior to traditional regression oriented approaches, such as regressing yield and soiltype or nutrient levels, that are being used in other research efforts. The advantage of this approach is that process oriented models, unlike regression models, can be used to evaluate the yield response resulting from changes in management practices in individual grids. This leads to the ability to compute optimum prescriptions including optimum planting date, plant population, and variety. Procedures outlined in this work can be extended to evaluate other models and other crops.

**Literature Cited**


