Determination of field capacity for the sugarcane harvester using GNSS data

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Abstract. Harvesting is an important activity in the sugar production industry. Due to the labor shortage and time limitation during harvesting season, farmers have adopted cane harvesters to substitute the farm workers in this restless period. Cane harvesters are huge and expensive machines with high field capacity. Because of inappropriate working conditions in Thailand, the actual field capacity is much lower than that in its specification. The objective of this research is to study the factors affecting the field capacity of the sugarcane harvester. A GNSS logging system was used to record the machine’s position and traveling speed during operation. Crop yield for each field was also collected. Field dimension and other working parameters such as working time and the number of turns were derived from the GNSS data. A field capacity prediction model was developed. The study shows that the optimal working speed, crop yield, and the number of turns per field area were significant factors to predict the harvester’s field capacity. The coefficient of determination (R² value) of the model was 0.625. It was suggested to include more machine and field variation for further robust model development and uses in the optimization of field operation performance.

1. Introduction
Due to a rise in the sugar demand in Thailand, the number of sugarcane farms has been continuously expanded, causing an increment of labor demand. In contrast, availability of farm workers has been diminishing every year. Also, harvesting season is typically limited for four months from December to March [1]. The labor shortage has become a severe problem to feed raw sugarcane into sugar production. One important solution is to use cane harvesters instead of conventional manual harvesting. Even though the harvesters are expensive, the number of cane harvesters has increased in most of the sugar production areas. Other modern farming machines have been increasingly adopted in the sugarcane industry from soil preparation to harvesting. These new technologies help to save time and cost of operations.

Sugarcane harvesters are very large machines with high harvesting capacity serving a significant solution for the labor shortage problem. To use these machine with success, many fields and operational factors affecting the machine performance such as crop yield, field size [2], traveling speed [3], field shape [4-5], and row length [6] must be considered. In Thailand, these parameters are typically not in ideal conditions and expensive to improve by farmers themselves. The extensive study of these factors would gain knowledge to support farmers, machine’s operators and sugar mill’s managers to plan and operate the in-field harvesting and the overall logistics at its best efficiency.
Unlike other manufacturing processes, it was not easy to collect the operational data at the field level. Conventionally, researchers use stopwatches, field tape, and many marking poles to help to collect the field and operational information. This technique is tedious and time-consuming. Also, the data collected was typically the overall numbers, which are not suitable for the optimization purpose.

With the advances in Global Navigation Satellite System (GNSS) technology [7], vehicle tracking systems have been developed and used for many logistic purposes. GNSS receivers could collect positioning and speed of the machine remotely making a convenience in further data analysis. Recently, the author [8] has developed a GNSS tracking system to record operational data of sugarcane harvesters automatically. The collected data could be used to classify the activities of the studied harvesters.

The objective of this research was to study factors affecting field capacity of a mechanical sugarcane harvester using GNSS and field data. Operational capacity tells the operators and farm managers when to finish the harvesting. This is an essential parameter for further optimization of the harvesting performance under specific local conditions.

2. Materials and Methods
Field capacity is a measure of agricultural machinery performance telling how fast is the field operations. By definition, it is the ratio of the working area to its operation time [5]. Factors affecting field capacity under the constraints of this study are as follows.

2.1. Theoretical capacity of the machine
The ideal ability of the machine is to operate the machine at its optimal speed with the perfect working width without any losses from other activities.

2.2. Field shape
The shape of the field influences the row direction in row crops and then the traveling pattern. It affects the number of turns. Figure 1 shows fields with the same size, but in four different shapes. Comparing to field A, field B has less number of turns due to its longer but narrower shape. For the case of field D, even the field size is the same as in field B, but the row orientation is in a transverse direction causing a higher number of turns at the headlands. The machine would spend more time in operation. In field C, its complex shape introduced more turns, causing more time to finish the field work. The number of turning per area or turning density is a standardized form that can be used as an index for the field performance analysis.

![Figure 1. Fields with the same size, but in different shapes](image-url)
2.3. Field size
In rectangular fields, length and width of the field affect the field capacity differently. Longer length allows the machine to focuses more on harvesting, not turning, resulting in higher field capacity. On the other hand, expanding the field width is only duplicating of the operation. Wider width does not affect the change in field capacity.

2.4. Machine maneuverability
It is the ease to move and work in the field, typically depending on the size matching between the machines and fields. Huge machines are typically cumbersome in turning at the headlands, especially in small fields. In this study, only one machine was used to study, so the variation in maneuverability was not compared.

2.5. Crop Yield
Crop yield affects the working capability of the machines. However, this depends on the power rating of the machines. Powerful machines could handle the harvesting task with ease up to their limitation. In the small machine, crop yield is a critical factor that defines the harvesting speed for specific fields.

2.6. Soil and crop conditions
It is obvious that the field capacity of the machine is limited by the ease or difficulty of the working environment from soil and crop conditions.

2.7. System limitations
Many other factors affect the machine capacity, such as availability of the loading trucks. The harvesting operation will be interrupted if the loading trucks are inadequate. This study was not accounted for this situation. Unusual cases were excluded from the dataset.

The agricultural machinery tracking system developed by Vasu et al. [8] was used to record the field activities of the participating harvester. Traveling speed, latitude, longitude, and course of travel of the harvester was recorded at 5 Hz rate. Figure 2 shows the components and diagram of the tracking system. Also, a small video camera was installed on the harvester's windshield to videotaping all activities for reference.

![Diagram of the tracking system](image)

**Figure 2.** The agricultural machinery tracking system.

Further field information could be extracted from the collected GNSS data. QGIS software [9] was used for data visualization and spatial analysis. Field size could be determined from the area covered by the recorded points. Since the number of fields were small, direct measurement of the field dimension parameters from the map was accurate but straightforward.
For the traveling speed determination, this study used the statistic mode of the speed value from the studying field, which is the most common traveling speed that the harvester used. It represented the most suitable speed under soil, crop, and other working conditions for each field.

Crop yield is the ratio between the weight of harvested sugarcane and its corresponding acreage. In harvesting operation, typically there are more than one loading trucks to gather the cane billets from the working harvester. Therefore, the total billet weight from all corresponding loading must be noted and summed.

The GNSS data combining with the physical data from each field were used for analysis. Those parameters were field capacity \( C \), optimum traveling speed \( S \), field size \( A \), number of turning \( T \), turning density \( TA \), row lengths (average, maximum, and minimum). Multiple linear regression (MLR) analysis with a stepwise selection method was used to select the parameters and develop the prediction model for the field capacity.

3. Results and Discussion

Data were collected by using the developed system to track operating cane harvesters (Austoft 340 HP, Australia) in 2016/2017 growing season in Nakhon Ratchasima province, Thailand (Pimai, Chakkrarat, and Huai Thalaeng districts). The data covered 26 fields. Figure 3 shows an example of the recorded data on the QGIS software.

Table 1 shows statistical descriptions of the studied parameters including field capacity \( C \), optimum traveling speed \( S \), field size \( A \), number of turning \( T \), turning density \( TA \), crop yield \( Y \), and row lengths (average, maximum, and minimum).

Multiple linear regression (MLR) analysis was performed using the R software [10]. From eight initial independent variables in table 1, only three variables, i.e., optimum traveling speed \( S \), turning density \( TA \), and crop yield \( Y \) were selected using stepwise selection technique as the significant parameters to predict the field capacity \( C \) represented in table 2 and equation 1.

\[
C = 0.378 + 0.449 \times S - 0.012 \times TA + 0.198 \times Y
\]  

(1)
Table 1. Statistical descriptions of the modelling factors.

| Descriptor | Minimum | Maximum | Average | SD. |
|------------|---------|---------|---------|-----|
| C (ha h\(^{-1}\)) | 2.54 | 1.07 | 1.89 | 0.34 |
| T (turn)    | 309.00 | 18.00 | 71.88 | 66.19 |
| A (ha)      | 9.83  | 0.38  | 1.81  | 1.95 |
| T\(_A\) (turn ha\(^{-1}\)) | 66.32 | 24.54 | 42.59 | 11.80 |
| S (km h\(^{-1}\)) | 5.20 | 2.60 | 3.65 | 0.70 |
| Y (ton ha\(^{-1}\)) | 3.15 | 0.92 | 2.02 | 0.49 |
| l\(_{\text{min}}\) (m) | 283.93 | 16.08 | 121.75 | 86.61 |
| l\(_{\text{max}}\) (m) | 414.48 | 134.62 | 224.56 | 69.61 |
| L\(_{\text{avg}}\) (m) | 283.93 | 78.36 | 169.96 | 59.27 |

Note: C = field capacity (ha h\(^{-1}\)), T = number of turns, A = area (ha), T\(_A\) = turning density (turns per area, turn ha\(^{-1}\)), S = optimum traveling speed (km h\(^{-1}\)), Y = yield (ton h\(^{-1}\)), l\(_{\text{min}}\) = shortest row length (m), l\(_{\text{max}}\) = longest row length (m), and L\(_{\text{avg}}\) = average row length (m).

Faster traveling speed and higher crop yield positively affected the field capacity. However, more turning per area caused the capacity to decrease. The coefficient of determination (R\(^2\) value) of the full and leave-one-out cross-validated models were 0.625 and 0.444, respectively. Figure 4 shows the scatter plot of the model.

Table 2. Characteristics of the descriptors selected in the optimal MLR model.

| Descriptor | Estimate | Std. Error | t-Value | t-Probability | VIF |
|------------|----------|------------|---------|---------------|-----|
| Intercept  | 0.378    | 0.426      | 0.889   | 0.384         |     |
| S          | 0.449    | 0.076      | 5.896   | 0.000         | 1.408 |
| T\(_A\)    | -0.012   | 0.004      | -3.032  | 0.006         | 1.161 |
| Y          | 0.198    | 0.104      | 1.896   | 0.071         | 1.295 |

*S = optimum traveling speed (km hr\(^{-1}\)), T\(_A\) = turning density (turn per area, turn ha\(^{-1}\)), Y = yield (ton ha\(^{-1}\))

Figure 4. Comparison between the predicted and actual field capacity.
4. Conclusions
The study shows that the optimal working speed, crop yield, and the number of turns per field area were significant factors to predict the harvester’s field capacity. The coefficient of determination ($R^2$ value) of the model was 0.625. It was suggested to include more machine and field variation for further robust model development and uses in the optimization of field operation performance.

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Acknowledgments
Researchers would like to thank the Korat industry Co. Ltd, Nakhon Ratchasima, Thailand for allowing to install the tracking systems and video recorders on the company’s sugarcane harvesters. The company also provided useful and necessary information for this study.