YIELD PREDICTION OF POTATO BY UNMANNED AERIAL VEHICLE

Dai TANABE[1], Shigeru ICHIURA[1], Ayumi NAKATSUBO[2], Takashi KOBAYASHI[2], Mitsuhiko KATAHIRA[2]

[1]*The United Graduate School of Agricultural Sciences, Iwate University*
[2]*Yamagata University*

Abstract
We built an analysis system that combined image data from UAV and Deep-Learning AI to investigate the relationship between image data and actual yield. The experiment was designed with 6 fertilizer treatments in the potato field, aerial images were obtained and plant growth and yield was measured. A potato yield prediction model was then built with AI on the basis of the aerial image and potato yield. Results showed a difference in plant cover between each plot, but no difference in NDVI value. Each fertilizer treatment produced a variation in plant growth as time progressed. There was a correlation between potato yield and NDVI value in etiolation stage. Yield prediction model accuracy with RGB image during the growth stage was the highest.

Keywords: *UAV; NDVI; IoT; AI; Potato.*

INTRODUCTION
At present, the number of agricultural workers is decreasing in Japan *(Ministry of Agriculture, Forestry and Fisheries, 2015)* and there is a concern that the agronomic technology that comes from experience will be lost. Therefore, new approaches such as robotization and introduction of AI (artificial intelligence) technology are being promoted. As part of that, UAV (Unmanned Aerial Vehicle) has been used as a new platform for efficiently acquiring information in the field. In addition, NDVI (None Differential Vegetation Index) is most commonly used as a vegetation index for evaluating the growth of plants from aerial images such as UAV. On the other hand, AI technology has been rapidly developed against the background of GPU (Graphics Processing Unit) and Big Data, and in the field of agriculture, attempts are being made to classify crop species at the field level and to detect disease of crops using deep learning (*Yaping, et al., 2018; Jun, et al., 2017*). However, since large amount of learning data is essential for accurate learning, only few cases have been reported in literature were AI was applied to yield prediction of land use type crops which have many fluctuation factors outdoors.
This research aims to establish a new method to predict potato yield by analyzing the data obtained from UAV with AI.

MATERIALS AND METHODS
Agricultural summary
The experiment was conducted at Takasaka Agricultural field centre of Yamagata University, located in Tsuruoka City, Yamagata Prefecture. The field dimensions were length 40m, width 7.5m, with an area of 300m^2. Test crop was potato (Solanum tuberosum L. "Toyoshiro") and was transplanted on May 1st 2018. The row spacing was 0.75 m, plant spacing 0.3 m and the planting density was 4.44 strains / m^2. 3kg /m^2 of barnyard manure, 100 g/m^2 of bitter lime, 40 g/m^2 of fused magnesium phosphate, 10 g/m^2 of heavy roasted phosphorus were spread as soil improvement material before transplanting. Base fertilization was 2 ~ 10 g-N/m^2 of chemical fertilizer (N: P_2O_5: K_2O= 14:14:14) and additional fertilization was 2 g-N/m^2 of ammonium sulphate. Additional fertilizer was applied on June 4.
UAV flights and aerial images
Aerial image was obtained by the multi-copter (S900, DJI) equipped with a multispectral camera (Micro MCA RGB+3, Tetracam). The shooting altitude was 30 m, and approx. 100 images were acquired. The aerial image was acquired with overlap rate was 75 % or more and the side wrap rate was 60 % or more. The ground resolution of the aerial image was approx. 0.015 m / pixel. The aerial photograph was obtained during 10:00 to 14:00 hrs after emergence of potato in each week. Individual plants were selected to measure growth in advance and set up some marks before the flight. Aerial images were processed with Pixel Wrench2 (Tetracam) and ortho-mosaic images built with Photoscan (Agisoft). Ortho-

mosaic images were evaluated and mapped by calculating NDVI. Moreover, the band values for each pixel was extracted from the ortho-mosaic image, it correlated with ground truth data and used for analysis of plant growth.

Construction of test area

Six test areas were created by combining the amount of base fertilizer and the additional fertilization in the test field described above: A) 10 g-N/m^2 of base fertilizer and 2 g-N/m^2 of additional fertilizer. B) Only 10 g-N/m^2 of base fertilizer. C) 6 g-N/m^2 of base fertilizer and 2 g-N/m^2 of additional fertilizer. D) Only 6 g-N/m^2 of base fertilizer. E) 2 g-N/m^2 of base fertilizer and 2 g-N/m^2 additional fertilizer. F) Only 2 g-N/m^2 of base fertilizer. Fig.1 showed the arrangement of each test field.

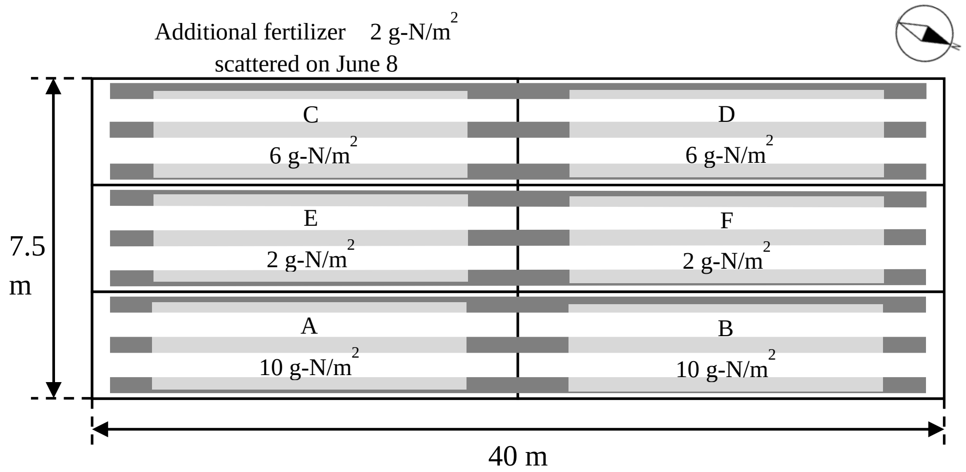


Fig. 1 Construction of test area

Plant growth survey

The plant growth survey was conducted on May 28, June 14, 25, July 9 in 2018. Three individual plants were selected in each survey area and the measurement parameters were plant height, total weight, and plant dry weight. In this report, only the data of plant height is published.

Yield survey

The potato harvest survey was conducted on August 6, 2018. Five survey plots of 1.8 m × 1.8 m were chosen in each test area of the field. 4 individual plants were harvested from each survey plot surveyed. The measurement parameters were total tuber weight (g) and number of tubers (piece).

Yield prediction

Multiple regression analysis based on growth data and deep learning artificial intelligence was used for potato yield prediction.

The statistical software R (ver. 3.5.1) was used for the multiple regression analysis with yield (g/m^2) as the dependent variable while the explanatory variables were the NDVI value and plant height for each growth survey.

The data set for construction potato yield prediction model was created as follows: 1) The plot portion used for the yield survey was cut from the aerial photographs of each growth stage from May to July 2018. 2) Plot portion image's angle was changed by 90, 180, 270, 360 degrees. 3) They were classified by yield (kg/m^2) calculated from the yield survey results. 4) Classified images were organized at each growth stage, and a total of 1080 images were used for training each time. 5) Images in which the left and right of the plot image were inverted were created and used as test data. The Chainer framework (ver. 1.23.0) and Alex Net neural network was used for building the AI with a batch size 32 and epoch number 100 used for learning.

RESULTS AND DISCUSSION

Aerial photographs

Fig.2 (a) shows RGB aerial images for each season. Aerial image of May 28 shows a clear difference in emergence due to difference in base fertilization condition. Area A and B had the strongest growth in the test field. On June 14, the difference in the size of the plant body and the size of the plant canopy due to variation in base fertilization is evident, also the difference in growth due to the presence or absence of additional fertilizer can be slightly confirmed in comparison with the area E and F. In the image taken on June 25, due to size of the canopy the space between the rows was obscured in area A and B. There was also a mixture of plants with respect to maturity and growth of secondary plants.

Fig.2 (b) shows NDVI aerial images for each stage. The height of the NDVI is expressed in grayscale, where white indicates high NDVI and black low NDVI. The image on May 28 is similar to the RGB image, and the difference in emergence can be confirmed clearly. Although the difference is not seen in NDVI. In the image on June 14, the difference is not seen in NDVI, In the image on June 25, there is a tendency for NDVI to be slightly higher in the high fertility area. In the image of July 9, NDVI appears to be uniform overall. The average NDVI value has changed each area: A) 0.62, 0.80, 0.74, 0.79. B) 0.64, 0.80, 0.77, 0.77. C) 0.64, 0.77, 0.68, 0.73.D) 0.58, 0.77, 0.77, 0.77. E) 0.53, 0.78, 0.75, 0.74. F) 0.57, 0.78, 0.75, 0.74. The same trend is observed in all treatment areas, but NDVI, which dropped by one in the third to fourth surveys, raised again. At the time of the third survey, most plants yellowed and NDVI decreased, but at the time of the fourth survey, new leaves with high photosynthetic activity had grown secondarily, and the NDVI levels increased.

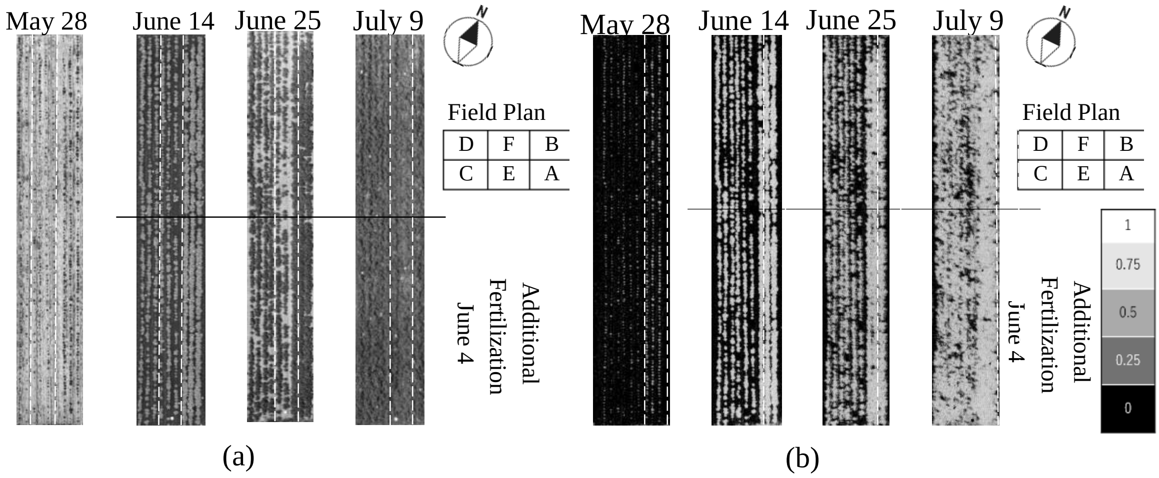


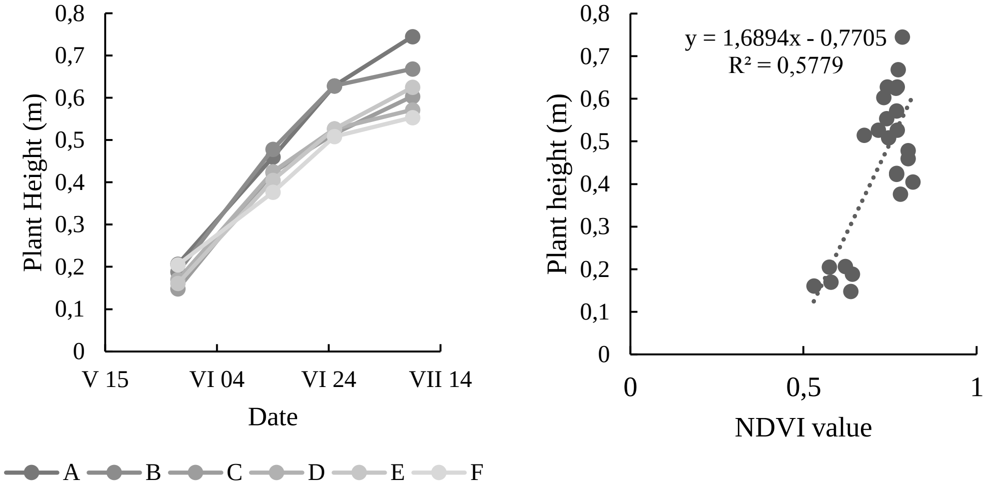
Fig. 2 The aerial image. (a) RGB aerial image; (b) NDVI aerial image.

Plant Growth Survey

The transition of plant height is shown in Fig.3 (a). The plant height has changed in each area: A) 0.21 m, 0.46 m, 0.63 m, 0.75 m. B) 0.19 m, 0.48 m, 0.63 m, 0.67 m. C) 0.15 n, 0.42 m, 0.52 m, 0.60 m. D) 0.17 m, 0.43 m, 0.53 m, 0.63 m. E) 0.16 m, 0.41 m, 0.53 m, 0.63 m. F) 0.21 m, 0.38 m, 0.51 m, 0.55 m. Although there was little difference in the growth survey during the early stages of growth in the test period, plant height increased during test interval in accordance with age and the amount of nitrogen applied. In addition, the growth rate of plant height was low at the fourth growth survey in the B, D, and F areas where no additional fertilization was performed, and the additional fertilization affected the growth of plant height at the later growth stage for areas A, C and E.

Fig.3 (b) shows the correlation between NDVI and plant height. The coefficient of determination R^2 was 0.58. The plant height and NDVI showed the higher correlation than the total weight and the plant dry weight (R^2 = 0.24, 0.41). This suggests that it is possible to construct a growth, yield prediction model using NDVI and the plant height as parameters.

According to the report of Hunt, E.R., et al., Potato with different nitrogen conditions tended to show no difference in LAI, NDVI, etc. during tuberization *(Hunt, E.R., et al., 2018)*. This is the same result for NDVI in this test. However, in the tests where nitrogen and phosphoric acid application conditions were changed respectively, it has been reported that frequent use of N and P promotes the increase of plant height and biomass etc. *(Zelalem, et al., 2016)*. Also in this test, there is a tendency that there is a difference in treatment area in plant height. It can be said that the effect of the difference in fertilization amount is larger in plant height than in NDVI.



(a) (b)

Fig. 3 The result of plant survey. (a) The transition of plant height; (b) The correlation of NDVI and plant height.

Table 1 shows the yield of potato and the number of tubers per individual plants in each test section. The total yield varied with the amount of fertilization mostly: A) 4230 g/m^2. B) 4371 g/m^2. C) 2543 g/m^2. D) 2913 g/m^2. E) 2936 g/m^2. F) 2061 g/m^2. Regarding the yield, the standard deviation tends to be high in B, D and F areas where no additional fertilization was performed. This indicates that the nitrogen supply at the late growth stage was insufficient due to the absence of additional fertilization, and the translocation of nutrients to the tuber was uneven.

Tab. 1 Yield and number of tubers

Area	Yield (g/m^2)	Number of Tubers
A	4230 (515.0)	10.3 (2.67)
B	4371 (1252.1)	12.5 (4.12)
C	2543 (667.5)	7.0 (3.25)
D	2913 (824.5)	7.8 (1.26)
E	2936 (343.6)	10.2 (1.44)
F	2061 (738.1)	8.3 (2.85)

Note: The numbers in parentheses indicate the standard deviation

The coefficient of determination between the NDVI value of each period and the yield is shown in Table 2. The yield of potato was highly correlated (R^2 = 0.67) with the NDVI value on July 9, and the number of tubers per individual plant was highly correlated with the NDVI value on June 14 (R^2 = 0.67). The flowering period of the potato corresponds to the tuber period, which was June 14 in this test. Therefore, the correlation between the NDVI value of this day and the number of tubers has increased. In addition, the fourth NDVI value has a strong correlation with the yield and the number of tubers because nitrogen absorption by secondary growth of plants affected tuber growth. For these reasons, the construction of potato yield prediction model with the potential to predict yield or number tubers, based on the aerial image of the plant at flowering or late growth stage is suggested.
Khalid et al. Examine the relationship between NDVI from satellites and potato yield, and report that they can be predicted with an accuracy of R^2 = 0.39 to 0.65 *(Khalid, et al, 2016)*. The accuracy in this research is R^2 = 0.02 to 0.67, which is the same as or lower than that of previous researches. These facts show that even with high-resolution aerial images, it is difficult to predict potato yield with only NDVI, and another method is needed to accurately predict potato yield.

Tab. 2 Coefficient of determination of NDVI value each of season and potato yield

R^2		Yield (g/m^2)	Number of tubers
NDVI	May 28	0.24	0.02
	Jun 14	0.31	0.67
	Jun 25	0.18	0.23
	Jul 9	0.67	0.47

Yield Prediction by multiple regression analysis

The results of multiple regression analysis of yield, NDVI value and plant height for each survey period are shown in Table 3.

The yield was predicted with high accuracy from the NDVI value and plant height on June 14 (early flowering season) and June 25 (late flowering season). This indicates that the growth of plant height at the flowering stage and the photosynthetic activity affect the yield.

Tab. 2 The results of multiple regression analysis

$Y=-4466.08+11380.94*X_1+46.96*X_2$ (May 28) $R^2=-0.1252$
$Y=-18851.5+11698.7*X_1+222.4*X_2$ (June 14) $R^2=0.9998$
$Y=-3397.2-3108.6*X_1+159.5*X_2$ (June 25) $R^2=0.8199$
$Y=-10917.02+11393.95*X_1+86.36*X_2$ (July 9) $R^2=0.5835$

Y: yield (kg/10a), X_1: NDVI value and X_2: Plant height (cm).

Yield prediction by Deep Learning

Fig.4 shows accuracy of yield prediction model based RGB image (a) and NDVI image (b). As shown in Fig.9 (a), the prediciton accuracy of each class is 12.2%, 50.2%, 37.1%, 60.3%, 5.1% in the growing stage, 2.5 %, 64.7 %, 46.8 % 37.3 %, 6.1 % in the flowering stage, 4.2 %, 22.1 %, 40.9 %, 28.3 %, 4.5% in the etiolation stage. On the other hand, as shown Fig. 9 (b), 5.7 %, 14.2 %, 25.4 %, 56.1 %,12.9 % in the growth stage, 0.0 %, 15.8 %, 45.1 %, 0.2 %, 0.1 % in the flowering stage, 4.2 %, 22.1 %, 40.9 %, 28.3 %, 4.5 % in the etiolation stage.

The RGB image-based model had better overall prediction accuracy than the NDVI image based one. Among those modelled on RGB images, the yield prediction accuracy at the growth stage and the flowering stage was higher than that the etiolation stage. The prediction accuracy was 33.0%, 31.5% and 20.0% in each stage. This caused no difference in plant canopy with the progress of time. Additionally, the accuracy rate of 1 - 2 kg/m^2 and 6 - 7 kg/m^2 classes were lower than any other classes. This was due to the number of data set being less than other classes.

The NDVI image-based model had a large difference in prediction accuracy depending on the stage. The prediction accuracy is biased to 4 - 5 kg/m^2 in growth stage, 3 - 4 kg/m^2 in flowering stage and 2 - 3 kg/m^2 in etiolation stage. This indicates that the model unable to differentiatie between plots, and NDVI image is not suitable to build a yield prediction model.

Therefore, RGB aerial image in growth or flowering stage is suitable for constructing a potato yield prediction model by Deep Learning. However, it is necessary to improve accuracy because Deep Learning model accuracy is lower than multiple regression analysis.

The low accuracy and bias of the prediction by AI in this test is due to the Imbalanced Data Set. There are two approaches to learning correctly with the Imbalanced Data Set. One is to assign high cost to minority class misclassification to minimize the overall cost, and the other is to adjust the number of samples by sampling. If the total number of data sets is small as in this test, it is considered that the former is applicable. In addition, accumulation of data sets will be required from now on.

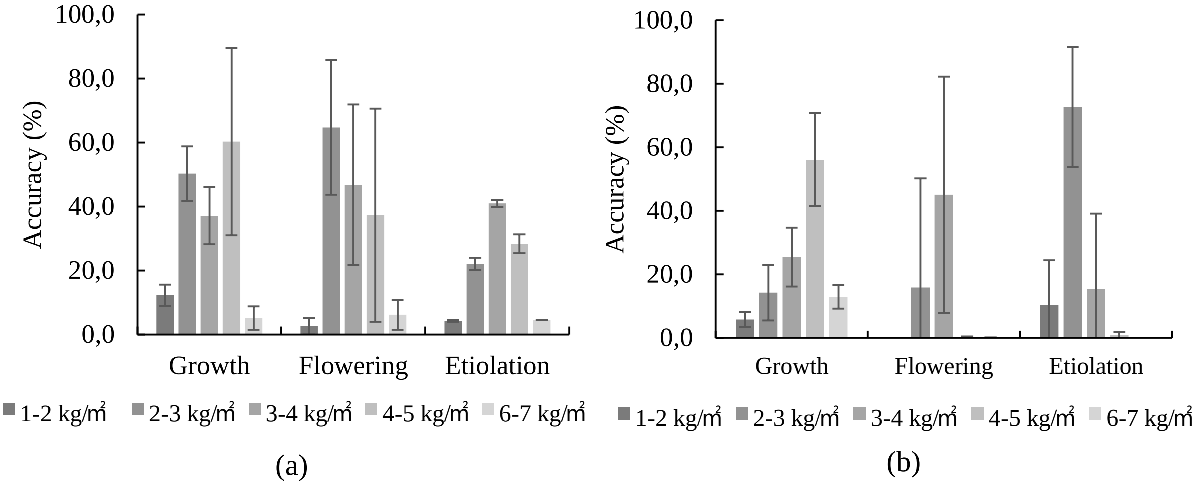


Fig. 4 Accuracy of the yield prediction model. (a) Based RGB image; (b) Based NDVI image.

CONCLUSIONS

This research was aimed at the establishment of the next generation of agriculture by IoT and tried to build a new monitoring system that combined aerial image data with UAV and analysis method by Deep Learning AI. The tests were conducted in the potato field under different fertilization treatments. The aerial image showed the difference of canopy by the difference of the fertilization treatment, but the difference was not seen in the NDVI value. NDVI value was correlated with plant height and the yield was correlated with the NDVI value in the yellowing stage, while the number of tubers were correlated with the NDVI value in the flowering stage. In the multiple regression model with NDVI value and plant height as explanatory variables and yield (g/m^2) as the target variable, the data at flowering stage gave high prediction accuracy. The yield prediction model with AI based RGB image in the growth stage was the highest prediction accuracy, but further improvement of this method is required.

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Corresponding author:
Dai Tanabe, The United Graduate School of Agricultural Sciences, Iwate University, Nishishinsai-machi, 10-35, Tsuruoka-city, Japan , 997-0045, tanabe.d.zc32s@gmail.com