A Feasibility Study of Precision Monitoring for Rice Field using Nanosatellites PlanetScope in Yangon Region, Myanmar

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Abstract: *Myanmar needs effective fertilization for increased rice yield and estimation of production for stable rice supply. Despite the large area of farmland, human resources are inadequate. Therefore, it is necessary to make a monitoring method using satellite imagery. The ground surface is often unobservable during the rainy season due to clouds. Therefore, this study evaluated the feasibility of a monitoring method using PlanetScope (SuperDove), which is one of the satellite constellations, can observe almost every day. The field study was conducted in two sites, Taikkyi in the northern part and Twantay in the southern part of the Yangon region. The variety in Taikkyi is Sin Thu Kha and Twantay is TBL. The number of survey points was 50 in each site. Field surveys were conducted approximately every two weeks from August to November 2023. Height and number of stems were measured before ear emergence, number of ears, ear length and culm length after ear emergence, and yield at harvest time. Despite the rainy season, PlanetScope were taken on the same day of the field survey or a few days apart. The PlanetScope product is an 8-band ground surface reflectance resampled to spatial resolution of 3 meters. The estimation model between satellite and field data was constructed by multiple regression analysis with green (band 4) and near infrared band (band 8). As a result, this method achieved an accuracy of 0.7 correlation coefficient for height and number of stems, and 0.8 correlation coefficient of yield. These results confirm that it is possible to estimate the growth of rice crop as a criterion for fertilizer application as well as rice crop yield even during the rainy season. By expanding these results to various varieties and districts, it is expected that a paddy rice monitoring method will be established for all of Myanmar.*

Keywords: rice crop monitoring, rice yield estimation, satellite constellation, PlanetScope, multiple regression analysis

Introduction

In Republic of the Union of Myanmar, paddy rice is not only important for food security as the main food for the Burmese, but also important for economic security as a major export commodity. Therefore, it is important for Myanmar agricultural corporation to reduce the cost of fertilizers, which affect the production cost of paddy rice, and to forecast the yield, which affects the food supply to their own people and the pricing of their exports. On the other hand, since various paddy rice varieties are planted in different regions of Myanmar, an economical and efficient method of monitoring for paddy rice is required. As part of these efforts, satellite data has been used to determine the area planted to paddy rice

(Torbick et al., 2017, Zhao et al., 2021) and to assess the loss of yield due to salt damage (Oo et al., 2017, Sakai et al., 2021). Kubota et. al. (2008) has also attempted to assess agricultural damage caused by cyclones in Myanmar using satellite data. In addition, monitoring methods using satellite data are being attempted from the perspective of conflict-induced food security (Huang et al., 2019). However, most of these studies were aimed at monitoring on a national scale, not the monitoring necessary for each district or field unit as required by the agricultural corporation. In addition, because variety yields in each field are not predicted, district yields are also only roughly estimated, it is difficult for agricultural corporation to compete appropriately on price in exports. This may be the low spatial and temporal resolution of the satellite data. With the recent development of nano-satellite constellations, high spatial resolution satellite images can be taken almost daily over most of the globe. In Japan, field-by-field monitoring of paddy rice using a satellite constellation of nanosatellites has been implemented (Odagawa and Okumura, 2018). In this study, we attempted to develop a paddy rice monitoring method for each field using PlanetScope (SuperDove) which is one of the nano-satellite constellations.

Methodology

The study areas are located in Taikkyi (about 60 km north of Yangon City) and Twantay (about 20 km west of Yangon City) in the northern and southern area of the Yangon Region, Myanmar. Study areas are shown in Figure 1. Both areas are located in the Irrawaddy Delta Plain. The Taikkyi area is affected by flooding, despite its distance from the tributaries of the Irrawaddy River. Twantay is located beside the canal connecting the Irrawaddy River to Yangon City. Both areas have irrigation facilities. The variety of Taikkyi is Sin Thu Kha and Twantay is TBL (Thee Baw Lay). In 2023, the cropping period in the study area is from early July to early August in Taikkyi and from late June to late July in Twantay. The harvest period was from late October to mid-November in Taikkyi and from mid-October to early November in Twantay. Both areas had both transplanted and direct seeded plots, but only transplanted plots were included in the analysis in this study. The reason for this is that planting density in direct seeding varies on the order of centimeters, and satellite image resolution cannot accommodate such complex heterogeneity. This is because there is a mixture of very high and very low planting density areas within a single pixel.

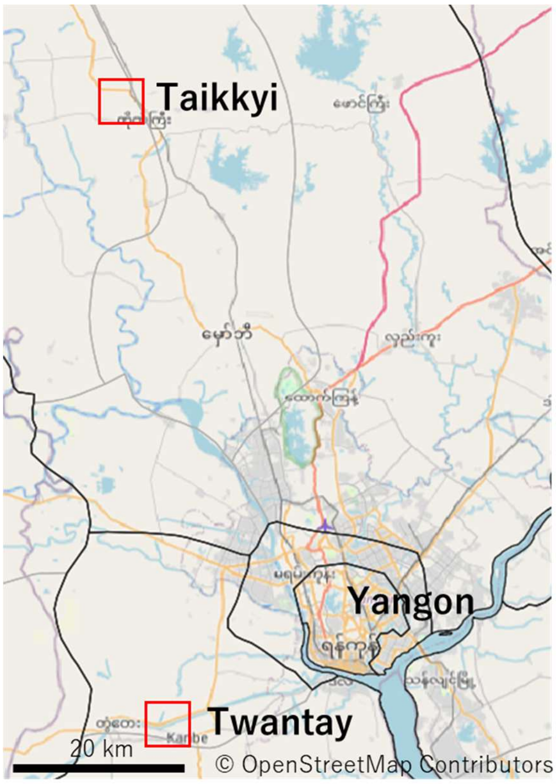

Figure 1: Study area.

The number of sites surveyed for this study was 50 in Taikkyi and 50 in Twantay, for a total of 100 sites. Each site was located to be representative of the paddy rice around each site and to take into account the heterogeneity of paddy rice in each area. Ten consecutive plants were included in the measurement at each site. The average of the measurements of these 10 plants was used as the data for each site. The location of each site was measured with a portable GPS. Positional accuracy of GPS is approximately 2 meters.

The field study period for this study was from mid-August to mid-November 2023, which is the rainy season in both areas. The interval between field surveys is approximately two weeks. Before ear emergence, grass height and number of stems were measured, and after ear emergence, number of ears, ear length, and culm length were measured. Yield at each site was also measured immediately prior to harvest. Models for estimating grass height and number of stem are used to examine appropriate fertilizer application. Ear number, ear length, and culm length have been noted to be related to paddy quality and yield (Matsue and Ogata, 1999), and these estimation models are used to confirm that fertilizer application was adequate and to examine quality and yield predictions.

Surface reflectance was measured using the nano-satellite constellation PlanetScope. PlanetScope's spatial resolution is approximately 3.7 to 4.2 meters. PlanetScope has eight bands of wavelength resolution: coastal blue (431 to 452 nm), blue (465 to 515 nm), green

1 (513 to 549 nm), green (547 to 583 nm), yellow (600 to 620 nm), red (650 to 680 nm), red edge (697 to 713 nm), near infrared (845 to 885 nm). PlanetScope's shooting interval is almost daily. In this study, ground surface reflectance products resampled to a spatial resolution of 3 m were used. The acquired date of the satellite image was the date closest to the date of the field survey.

The method of analysis in this study is multiple regression analysis. In this study, *lm* function included in *stat* package in statistical software *R* was used. Although multiple regression analysis may be a simple method compared to AI and machine learning, it is considered suitable for a simple evaluation of feasibility study because it allows the construction of estimation models even with a small number of samples and also allows easy interpretation of the estimated models. The correlation between each feature of paddy rice and the satellite-acquired surface reflectance was determined by multiple regression analysis. In the multiple regression analysis, explanatory variables were selected based on the multicollinearity of features of paddy rice as variables. In this study, the correlation was used as an estimation model to obtain each feature of paddy rice from satellite data. The accuracy of the estimated model was evaluated by the correlation coefficients obtained by multiple regression analysis.

Results and Discussion

The number of measured points for each field survey date in both areas are shown in Table 1. The observation dates of the satellite images applied to the data for each measurement date are also listed in Table 1. In both areas, grass height and stem counts were measured before ear emergence, and sufficient quantities of ear number, ear length, and culm length were measured after ear emergence for analysis. Due to local conditions, some of the measurement points could not be measured. In addition, yields at most sites could be measured before the harvest.

Table 1: The number of measurements points each time with acquisition date of PlanetScope.

Taikkyi 2023	**Week1 8/10~12**	**Week2 8/29~30**	**Week3 9/13~14**	**Week4 9/27**	**Week5 10/12~13**	**Week6 10/27**	**Week7 11/10or13**
Height	50	50	50	49	49	29	20
N. Stem	50	50	50	49	49	29	20
N. Ear	NA	NA	3	11	32	29	20
Ear length	NA	NA	3	11	32	29	20
Calm length	NA	NA	3	11	32	29	20
Yield	NA	NA	NA	NA	NA	49	
SuperDove	8/20	8/30	NA	9/26	10/14	10/25	11/3or11

Twantay 2023	**Week1 8/11~17**	**Week2 9/8**	**Week3 9/21~22**	**Week4 10/5~9**	**Week5 10/19~20**	**Week6 11/1~2**
Height	50	50	50	50	30	30
N. Stem	50	50	50	50	30	30
N. Ear	NA	26	40	50	30	30
Ear length	NA	26	40	50	30	30
Calm length	NA	26	40	50	30	30
Yield	NA	NA	NA	NA	50	
SuperDove	NA	NA	9/25	10/14	10/20	11/1

NA: Not Available

Multicollinearity was checked in each data set as the choice of explanatory variables for multiple regression analysis. Multicollinearity was checked and found to be multicollinear in bands 1 through 7 of the PlanetScope on all survey dates. As an example, a paired diagram of each band in week 5 is shown in Figure 2. The results showed a high correlation from bands 1 to 7. On the other hand, there was no strong correlation between band 8 and the other bands. Therefore, we decided to perform a multiple regression analysis using band 8 and another band. Comparing the reflectance of bands 1 through 7, band 4 has the highest reflectance and can be assumed to have a relatively high signal-to-noise ratio. Therefore, a multiple regression analysis combining band 4 and band 8 was used in this study.

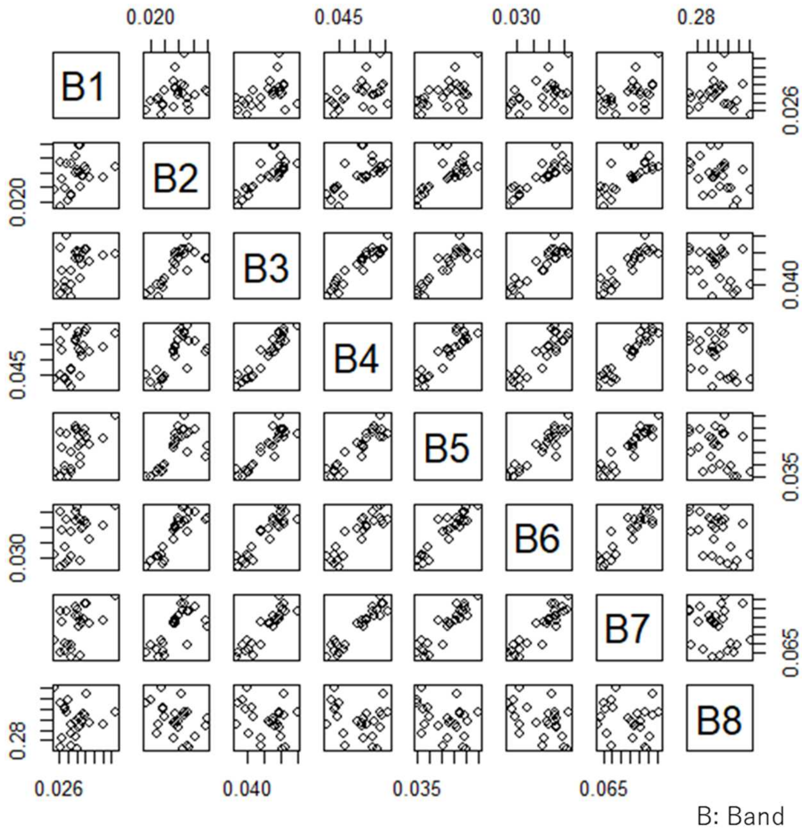

Figure 2: An example of pare diagram of PlanetScope (week5 in Taikkyi).

The correlation coefficients between the features of paddy rice and satellite data in both areas are shown in Table 2. In Taikkyi, the maximum correlation coefficient for grass height was 0.64 (50 measurements) and the maximum correlation coefficient for number of stems was 0.65 (50 measurements) before ear emergence. In Twantay, satellite data could not be obtained before ear emergence, but the correlation coefficient for grass height was 0.72 (50 measurements) and the correlation coefficient for number of stems was 0.61 (50 measurements) at the ear emergence stage. In Taikkyi, the maximum correlation coefficient for number of ears was 0.71 (32 measurements), for ear length 0.72 (20 measurements), and for culm length 0.76 (20 measurements) after ear emergence. In Twantay, the maximum correlation coefficient for ear number was 0.69 (40 measurements), for ear length 0.75 (20 measurements), and for culm length 0.71 (50 measurements) after ear emergence. Those results suggest that both areas were able to construct estimation models with some accuracy for grass height and stem number before ear emergence stage, as well as for the number of ears, ear length, and culm length after ear emergence stage.

Table 2: Correlation coefficients between rice paddy features and satellite data.

Taikkyi 2023	Week1 8/10~12	Week2 8/29~30	Week3 9/13~14	Week4 9/27	Week5 10/12~13	Week6 10/27	Week7 11/10or13
Height	0.5	0.64	NA	0.27	0.63	0.73	0.75
N. Stem	0.65	0.4	NA	0.31	0.31	0.21	0.3
N. Ear	NA	NA	NA	0.53	0.71	0.43	0.64
Ear length	NA	NA	NA	0.48	0.39	0.6	0.72
Calm length	NA	NA	NA	0.43	0.31	0.75	0.76
Yield	NA	NA	NA	NA	0.81	0.57	0.49

Twantay 2023	Week1 8/11~17	Week2 9/8	Week3 9/21~22	Week4 10/5~9	Week5 10/19~20	Week6 11/1~2
Height	NA	NA	0.72	0.75	0.52	0.06
N. Stem	NA	NA	0.61	0.46	0.54	0.29
N. Ear	NA	NA	0.69	0.21	0.33	0.26
Ear length	NA	NA	0.64	0.65	0.75	0.7
Calm length	NA	NA	0.62	0.71	0.58	0.06
Yield	NA	NA	NA	0.52	0.28	0.21

NA: Not Available

In the yield estimation model building, the best estimation model was attempted to build from yield data measured during the harvest season and satellite data from several time periods that could be obtained before the harvest season. The reason for this approach was to explore the possibility of predicting yields as early as possible while ensuring some estimation accuracy, and to examine the optimal time to obtain the best yield prediction accuracy. The select of explanatory variables is a combination of band 4 and band 8, as with grass height and others. The results showed that both districts had the highest accuracy, with correlation coefficients of 0.81 for Taikkyi and 0.52 for Twantay, approximately two weeks before the start of the harvest season. In both areas, the accuracy of the estimates decreased as the harvest season approached. This suggests that the best time to estimate yields is two weeks before the harvest season begins, despite the different districts and varieties. As the rice plants mature, they turn yellow. This is thought to be because all rice plants of different yields change into the same yellow.

On the other hand, the results also showed that estimation accuracy was not stable in the same area. The survey periods with the highest accuracy in estimating grass height and stem count were different in Taikkyi. The highest correlation coefficient for grass height before ear emergence was in late August, while the highest correlation coefficient for number of stems was in mid-August. Moreover, in mid-August, when the correlation coefficient for the number of stems was high, the correlation coefficient for grass height was low, and in late August, the correlation coefficient for grass height was high while the correlation coefficient for the number of stems was low. Before ear emergence, grass height continues to increase, but the number of stems may increase and then decrease after the maximum tillering period. Under these characteristics of rice growth, the appropriate time period for building a model for estimating grass height may differ from the appropriate time period for building a model for estimating stem number. In such cases, it will be necessary to select items to be measured according to the growth of the crop. In the future, it will be necessary to have a method to determine the timing of cropping from satellite data. In the post-emergence period, the highest correlation coefficient for the number of ears was in mid-October, but the correlation coefficient for ear length and culm length at that time was very low. The highest correlation coefficients between ear length and culm length were observed from late October to mid-November before harvest. This is in harmony with the fact that although ears emerged relatively early after ear emergence period, ear length and culm length continued to increase thereafter. This result also suggests that the need to select items to be measured according to growth will also arise, and therefore, in the future, technology to determine the timing of ear emergence from satellite data will also be necessary.

In Twantay, satellite data was not available prior to ear emergence, so this will be a post-ear emergence study. Twantay, as well as Taikkyi, has the highest correlation coefficient for ear number in late September after ear emergence, after which the correlation coefficient decreases. Similar to Taikkyi, the correlation coefficient for ear length was also highest in mid-October, before the harvest season. However, the correlation coefficient for culm length was slightly different from that of Taikkyi and was highest in early October, which was between ear emergence and harvest. Similar results were obtained in Taikkyi and Twantay, which are located in different districts, suggesting that a highly accurate estimation model can be constructed by acquiring data for each paddy feature at the appropriate time. Since this is only the first year of this study, more data needs to be accumulated to confirm whether such results can be obtained stably over year.

In this study, we applied the estimation model to the entire satellite image and produced a prototype estimation map of each paddy feature. As an example, the estimation maps of height, number of stems and yield in Taikkyi are shown in Figure 3. Note that paddy fields that were affected by clouds on the acquisition date were excluded. The distribution maps are the results for each paddy feature for the acquisition date when the highest correlation coefficient was obtained. The results may intend the heterogeneity of each feature of paddy rice within the field as well as the district in both areas. On the other hand, direct seeded fields may have overestimated the paddy features. Since this estimation model was constructed for transplanted fields, it is clear that it cannot be applied to direct-seeded fields, where planting density is fundamentally different from transplanted fields. Therefore, in the future, it is necessary to construct a model to distinguish between transplanted and direct-seeded fields in order to avoid applying this model to inappropriate fields.

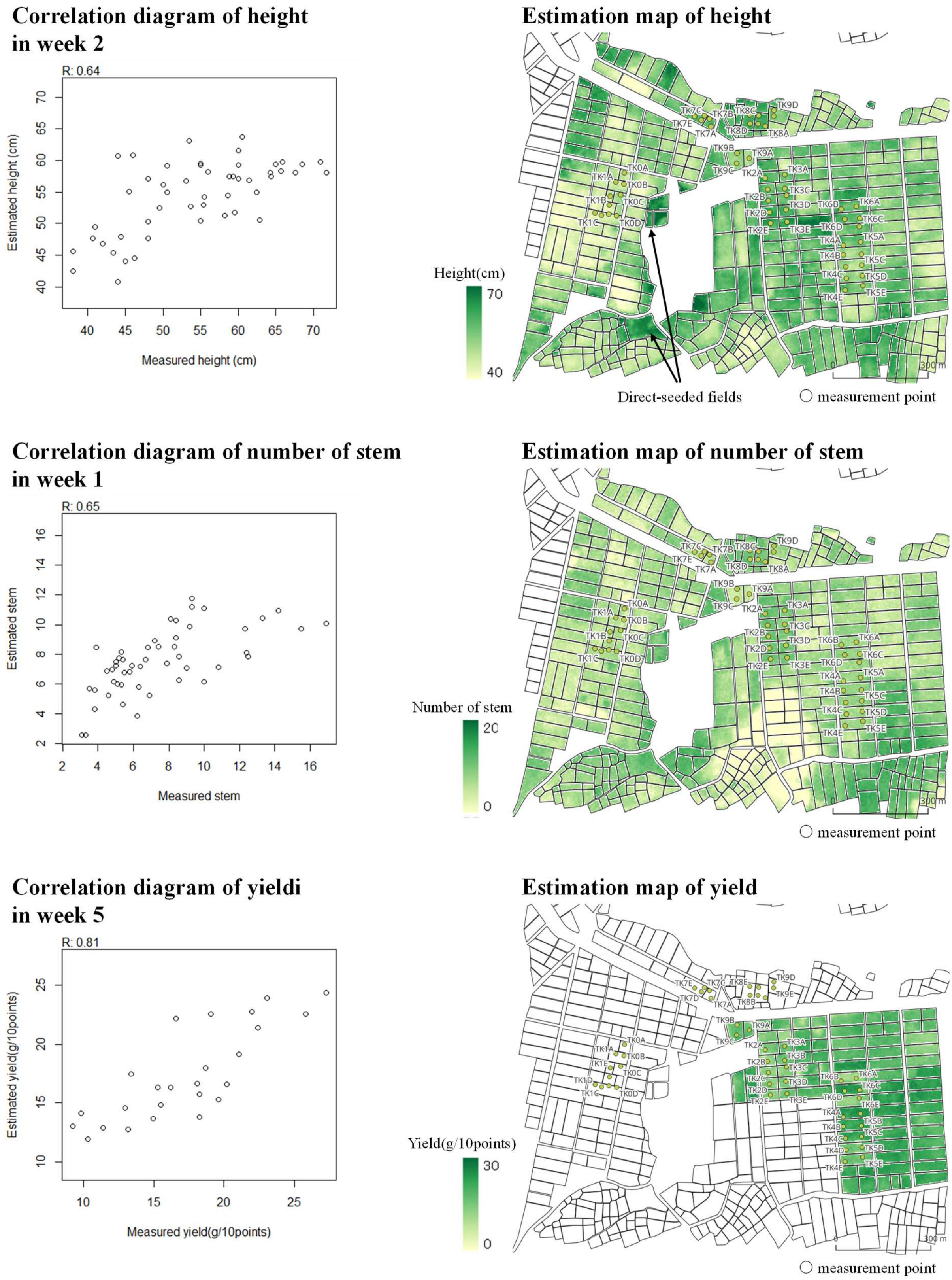

Figure 3: Estimation maps with correlation diagram in Taikkyi.

Conclusion

This study suggests the possibility of building models for estimating pre-emergence grass height and stem number, post-emergence ear number, ear length, and culm length, as well as pre-harvest yield prediction models for monitoring paddy rice growth for a particular variety in a particular district. If this estimation model can be put into actual operation, it is expected that the adequate amount of fertilizer can be applied at the optimum time, thereby reducing labor and costs. Early prediction of yield is also expected to contribute to appropriate pricing of paddy rice.

On the other hand, the results of this study were obtained only in a limited number of districts; therefore, in order to extend the results to the whole of Myanmar, the study should be conducted in the future in districts with different climates, soils, and water availability for various varieties. In addition, it is necessary to confirm the applicability of the results of this study over time and to show that it can be applied to recent climate changes, which are changing from year to year, by continuing this research.

In this study, linear regression was applied as the analysis method, which can construct an estimation model even with a small number of samples, but by aligning data from various districts and varieties over time, the factors necessary to construct a prediction model common to districts and varieties can be applied to mixed models, AI, and machine learning, which require a certain amount of data. By applying these factors to the data, detailed estimation models can be expected to be built.

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