Assessment of Multimodel Ensemble Seasonal Hindcasts for Satellite-Based Rice Yield Prediction

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Abstract

Several pre-harvest rice yield estimation methods have often failed to accurately estimate rice yields due to weather variability. We attempted to assess the APEC Climate Center Multimodel Ensemble (APCC MME) seasonal hindcasts to a satellite-based rice yield prediction model to timely provide estimates of rice yields for efficacious intervention plans. The developed model by a multiple regression analysis is \( \text{Yield} = 5.635 \text{NDVI} - 0.0012P_9 + 0.91 \) (where \( \text{yield} \) is the white rice yield in t ha\(^{-1}\) and \( P_9 \) is the observed monthly precipitation in September in mm month\(^{-1}\)). The goodness-of-fit measures were 0.66, -0.14%, 0.13 t ha\(^{-1}\), and 2.25%, for adjusted \( R^2 \) (coefficient of determination), Percent bias (PBIAS), Root Mean Square Error (RMSE), and Mean Absolute percentage Error (MAPE), respectively. A statistical downscaling method using Empirical Orthogonal Function Analysis (EOF) and Singular Value Decomposition Analysis (SDVA) was used to predict monthly precipitation hindcasts in September required for the developed model. Even though the estimates of rice yield using the predicted monthly precipitation for whole study period were not as good as the estimates using the 9.15 sampling method, the estimates for the two years of 2008 and 2009, when the 9.15 sampling method largely underestimated, were better than those using the 9.15 sampling method. It is concluded that the proposed approach can be used to timely provide rice yield estimates that reflect the meteorological conditions for more effective intervention plans in the rice market.

Key words: MODIS \text{NDVI}, MME (Multimodel Ensemble), Rice Yield, Statistical Downscaling.

I. Introduction

Rice (\( \text{Oryza sativa} \) L.) is one of the most important crops as a staple food crop for more than half of world’s population. Rice yields have been estimated and reported based on various methods including sampling methods, remote sensing techniques, empirical-statistical methods, and crop growth modeling so that estimates of rice yields can be used in plans for managing supply and demand, and price stabilization of rice. Timeliness, in addition to accuracy, for rice yield estimations is very important for efficacious intervention plans (Bastiaanssen and Ali, 2003; Hayes and Decker, 1996; Reynolds et al., 2002). Traditional crop yield estimations, like a sampling method which typically collects the required data from ground-based field visits is often subjective, costly, and can contribute to appreciable errors in the estimation (Reynolds et al., 2000).

There have been studies on estimation of crops using Vegetation Indices (VIs) derived from remotely sensed data (e.g., Kogan et al., 2013; Li et al., 2011; López-Lozano et al., 2015; Mkhabela et al., 2005; Mkhabela et al., 2011; Müller et al., 2008). For example, Panda et al. (2010) estimated corn yields using Normalized Difference Vegetation Index (\( \text{NDVI} \)). Bolton and Friedl (2013) used \( \text{NDVI} \) and Enhanced Vegetation Index (EVI) to estimate corn and soybean yields. In several studies, Land Surface Temperature (LST) with \( \text{NDVI} \) was used for crop yield estimation (Doraisswamy et al., 2007; Prasad et al., 2007). There have been studies on the estimation of the rice yields using satellite-derived \( \text{NDVI} \) (Huang et al., 2013; Hong et al., 2012; Mkhabela et al., 2011). Since this estimation is typically made with a lead-time of several weeks before harvest, crop yields can be poorly estimated due to weather variability during this period (Hayes and Decker, 1996). Observed meteorological variables with \( \text{NDVI} \) were used to improve crop yield estimation by reducing the weather variability. This approach has been used for winter wheat yield (Heremans et al., 2015) and for rice yield estimation (Hong et al., 2012; Na et al., 2012). However, this approach using observed meteorological variables may not be appropriate for the timeliness of the estimation because the meteorological variables collected during ripening period are not available until close to harvest.

Seasonal climate forecasts may be useful to overcome this shortcoming by replacing those observed meteorological variables. Seasonal climate forecasts have been used to agricultural applications. Lobell et al. (2007) suggested that crop yield losses may be substantially reduced by accurate seasonal climate forecasts. Multimodel ensemble (MME) techniques have been used to produce skillful seasonal forecasts by reducing uncertainties in the individual global climate model (e.g., Krishnamurti et al., 1999; Palmer and Shukla, 2000). The Asia-Pacific Economic Cooperation Climate Center (APCC) has produced 6-month lead predictions based on a fully operational MME seasonal forecast system since 2005 (Min et al., 2009).

The objectives of this study were to develop a MODIS-based model to more accurately estimate rice yields reflecting the meteorological conditions and to apply the APCC MME seasonal...
hindcasts for the developed model to timely provide the estimates of rice yield.

2. Materials and Methods

2.1 Study region and data collection

NDVI and the meteorological conditions were used to develop a rice yield estimation model in South Korea. The Korean government has reported white rice yield (hereinafter referred to as rice yield) estimates based on a sampling method (denoted by the 9.15 sampling method). Various information including the number of hill m², the number of effective panicles per hill, the number of filled grains per panicle, and any damages on rice plants is collected from over 3300 sampling fields for about a week from September 15 (KREI, 2011a). Both the estimates by the 9.15 sampling method and observed rice yields in South Korea were collected from Korean Statistical Information Service (KOSIS, http://kosis.kr) for this study. MODIS (Moderate Resolution Imaging Spectroradiometer) NDVI products (MODIS tile numbers h27v04, h27v05, and h28v05) were collected from Land Processes Distributed Active Archive Center (LP DAAC, https://lpdaac.usgs.gov/) for this study. The 16-day composite NDVI products at 1-km resolution from the Aqua satellite were provided from the year 2002. Considering the sizes of rice paddy field in Korea, finer resolution (at least 1-km resolution) of NDVI products was required to accurately calculate NDVI values at rice paddy fields in Korea. The Global Inventory Modelling and Mapping Studies (GIMMS) Normalized Difference Vegetation Index (NDVI) datasets (https://daac.ornl.gov/ISLSCP_II/guides/gimms_ndvi_monthly_xdeg.html) might not be appropriate for this study due to their coarse resolutions (i.e., 0.25, 0.5, and 1.0 degree).

For this study, observed meteorological datasets collected from Automated Surface Observing System (ASOS) operated by Korea Meteorological Administration (KMA) were used to reflect meteorological conditions (Lee and Lee, 2016). The 61 sites of ASOS which have longer than 30 years of meteorological datasets were selected to collect the observed precipitation, sunshine hours, and temperatures (Fig. 1) which are widely known to influence crop yields. These meteorological variables in August, September, October, and an average of these three months were collected to cover the period after the representative heading stage through ripening stage. The cultivated area of mid-late maturing rice cultivars in Korea in the year 2009 accounts for approximately 84.4% of the total rice paddy fields in Korea, followed by early maturing rice cultivars (about 10.9%) and mid maturing rice cultivars (about 4.7%). Odaebyeo and Ungwangbyeo are major cultivars in early maturing rice cultivars in Korea, Hwahyeongbyeo and Sura-byeo in mid maturing rice cultivars, and Dongjin1ho, Chucheongbyeo, Nampyeongbyeo, Junambyeo, and Ilmibyeo in mid-late maturing rice cultivars. The heading stages of the major cultivars (i.e., mid-late maturing rice cultivars) in Korea generally ranged between Aug. 12 and Aug. 23, and 50 to 55 days after the heading

Fig. 1. Location map of ASOS (Automated Surface Observing System).
stages are generally recommended to harvest for these cultivars. The representative heading stage of the major cultivar in Korea is Aug. 20 (Lee et al., 2010).

These datasets from 1983 to 2013 were collected for this study considering the archives of \( NDVI \) products (from 2002 to 2013) and the APEC Climate Center (APCC) Multi-Model ensemble (MME) hindcasts (from 1983 to 2010). The \( NDVI \) products and the observed meteorological variables from 2002 to 2013 were used to develop a rice yield estimation model. The APCC MME hindcasts from 1983 to 2010 were used to statistically predict those meteorological variables through a statistical downscaling method in this study. To investigate the applicability of the APCC MME hindcasts, a study period from 2002 to 2010 when both the \( NDVI \) products and the APCC MME hindcasts were available were selected for this study.

### 2.2 Rice yield estimation model

To calculate \( NDVI \) at rice paddy fields in Korea, a mask map (30-m resolution) for rice paddy fields was extracted using a land use map provided by EGIS (Environmental Geographic Information System, http://egis.me.go.kr). Little (only 0.0006%) change in area of rice paddy fields was observed at the 30-m resolution mask map after the vector map of rice paddy fields were converted into a raster format. However, it should be noted that the mask map does not reflect any changes in land use over the study period, implying that an inaccurate mask map leads to some errors in the rice yield estimation. Therefore, it is suggested that a more accurate rice paddy field mask map over the study period should be developed for a further study to improve the rice yield estimation model. The \( NDVI \) values at each rice paddy grid (30-m resolution) of this mask map were extracted using ArcGIS software package (ESRI, 2007) and averaged over the country. Since the 30-m resolution rice paddy mask used for the extraction can be described as a mask which consists of 30 m by 30 m rice paddy fields, all of the \( NDVI \) values in the 30 m by 30 m rice paddy fields contributed to the calculation of the average of \( NDVI \) values of rice paddy in the country.

A multiple regression analysis was used to develop the rice yield estimation model, since \( NDVI \) and meteorological variables (precipitation, maximum and minimum temperatures, and sunshine hours) were used as the predictor variables. The annual yields of rice for South Korea from 2002 to 2013 were used as response variable (i.e., the number of samples = 12). The PROC REG procedure of the SAS software package (The SAS system for Windows, 9.2, SAS Institute Inc., Cary, NC, USA) was used for this analysis. The stepwise selection method implemented in the PROC REG procedure was used for the selection of the predictor variables. This stepwise process in the PROC REG procedure identifies the predictor variables with an F statistic significant at the 0.15 level (SAS Institute Inc., 2011). The Leave-One-Out cross-validation method was conducted for the robustness of the model.

The performance of the rice yield estimation model was assessed with a few of goodness-of-fit measures including Percent bias (\( PBIAS \), eq. (1)), Mean Absolute Percentage Error (\( MAPE \), eq. (2)), adjusted \( R^2 \) (coefficient of determination), and Root Mean Square Error (\( RMSE \), eq. (3)).

\[
PBIAS = \frac{\sum_{i=1}^{n} (O_i - P_i)}{\sum_{i=1}^{n} O_i} \times 100
\]

\[
MAPE = \frac{100}{N} \sum_{i=1}^{n} \left| \frac{O_i - P_i}{O_i} \right|
\]

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (O_i - P_i)^2}{N}}
\]

where \( O_i \) is the observed value and \( P_i \) is the predicted value.

### 2.3 Prediction of the predictor variables

To apply the APCC MME hindcasts for the developed rice yield estimation model, a statistical downscaling method was used to predict the selected predictor variables for replacing the observed meteorological variables in the developed model. The APCC MME hindcasts were used to increase availability of the rice yield estimates for the intervention plans by timely providing the estimates of rice yields. Even though the 17 Global Circulation Models (GCMs) were generally used for the APCC MME technique, we had to select the GCMs to have the longest period since the year 2002 when the MODIS \( NDVI \) products from the Aqua satellite are available. The 6 GCMs including APCC-CCSM3 (APCC, Korea), MSC_CANCM3 (MSC, Meteorological Service of Canada, Canada), MSC_CANCM4 (MSC, Canada), NASA

| Institute     | Model name   | Resolution at Equator | Ensemble member |
|---------------|--------------|-----------------------|-----------------|
| APCCC         | APCC-CCSM3   | T85L26                 | 10              |
| MSC           | MSC_CANCM3   | T63L35                 | 10              |
| MSC           | MSC_CANCM4   | T63L35                 | 10              |
| NASA GSFC     | NASA         | 288×181L72             | 9               |
| PNU           | PNU          | T42L18                 | 10              |
| BOM           | POAMA        | T47L17                 | 30              |

\( ^T \) = spectral resolution and "L" is the number of model levels.

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large-scale atmospheric predictor variables required for the rice yield estimation model developed in this study. More detailed tor, and a noise filtering technique in the statistical downscaling method. perspective EOF modes and principal components were employed as predictor variables. These predicted variables will replace the selected predictor variables in the rice yield estimation model and the observed meteorological variables. To reconstruct the time series of large-scale variables, their respective EOF modes and principal components were employed as a noise filtering technique in the statistical downscaling method. SDWA was then applied to obtain coupled modes between the large- and station-scales. The following downscaling transfer function was constructed.

\[ PR\left( t, x \right) = \sum_{i=1}^{n} S_i\left( t \right) R_i\left( x \right) \]  

where \( PR\left( t, x \right) \) is the downscaled prediction, \( S_i\left( t \right) \) is the time expansion coefficient of the \( i \)th SVD mode for large-scale predictor, and \( R_i\left( x \right) \) is the singular vector of the predictand in the \( i \)th mode. For this study, \( n \) is equal to 10 (i.e., the first 10 leading modes for the large-scale variables were retained). The skill of the downscaling method was evaluated through leave-one-out cross-validation.

Through this statistical downscaling method, station-scale meteorological predictand variables were statistically predicted from large-scale atmospheric predictor variables required for the rice yield estimation model developed in this study. More detailed information on the statistical downscaling method can be found in Kim et al. (2004) and Chu et al. (2008). These predictors used for this study were SLP (See-Level Pressure), T2M (temperature at 2 m), T850 (850 hPa temperature), U200 (200 hPa zonal wind), U850 (850 hPa zonal wind), V200 (200 hPa meridional wind), V850 (850 hPa meridional wind), and Z500 (500 hpa geopotential height).

3. Results and Discussion

3.1 Rice yield estimation model

We investigated the correlation coefficients between NDVI on day-of-year (DOY) 201, DOY 217, and DOY 233 and rice yields from 2002 to 2013. The highest correlation coefficient (approximately 0.7) was found on DOY 233 followed by that (approximately 0.3) on DOY 217 and that (approximately -0.2) on DOY 201. This result is in substantial agreement with that by Hong et al. (2012). They reported that the highest correlation coefficient between NDVI on DOY 233 and rice yields was about 0.62. This day is close to the representative heading stage of mid-late maturing rice cultivars (i.e., Aug. 20) which are major cultivars in Korea (Hong et al., 2012).

The rice yield estimation model (eq. (5)) was developed using NDVI and the observed meteorological datasets from 2002 to 2013 and compared with the rice yield estimation model (eq. (6)) using only NDVI to investigate if the inclusion of the observed meteorological variables leads to the improvement of the rice yield estimation model using only NDVI (eq. (5)). The annual yields of rice from 2002 to 2013 (i.e., the number of samples = 12) were used as response variable for the models (eqs. (5) and (6)).

\[ Yield = 5.635\text{NDVI} - 0.0012P_9 + 0.91 \]  

\[ Yield = 6.983\text{NDVI} - 0.294 \]  

where \( Yield \) is the rice yield in t ha\(^{-1}\), \( NDVI \) is the 1-km resolution NDVI on DOY 233, and \( P_9 \) is the observed monthly precipitation in mm month\(^{-1}\) in September. The adjusted \( R^2 \) values were approximately 0.66 and 0.43 for the cases using NDVI and the observed meteorological variables (i.e., the model of eq. (5)) and using only NDVI (i.e., the model of eq. (6)), respectively. This adjusted \( R^2 \) value for eq. (5) was slightly lower than that (\( R^2 = 0.80 \)) of Hong et al. (2012) and higher than that (adjusted \( R^2 = 0.37 \)) of Na et al. (2012). These equations showed that NDVI has a positive correlation with rice yields, while monthly precipitation in September has a negative correlation with rice yields. These results are in substantial agreement with those of Hong et al. (2012) and Na et al. (2012). The \( P \)-values were 0.0031 and 0.0126 for eqs. (5) and (6), respectively. The RMSE value between the observed and estimated (using eq. (5)) rice yields was 0.13 t ha\(^{-1}\), while that between the observed and estimated (using

| Table 2. Goodness-of-fit measures for the regression models against observed rice yields. |
|-------------------------------|-----------------|-----------------|-----------------|
| Model                        | Sim. (VI)\(^{†}\) | Sim. (VI, ASOS)\(^{‡}\) | Est. (9.15)\(^{§}\) |
|-------------------------------|-----------------|-----------------|-----------------|
| PBIAS (%)                     | -0.34           | -0.14           | 0.97            |
| RMSE (t ha\(^{-1}\))          | 0.19            | 0.13            | 0.14            |
| MAPE (%)                      | 2.79            | 2.25            | 2.10            |

\( † \) Sim. (VI): estimated rice yield with only NDVI.
\( ‡ \) Sim. (VI, ASOS): estimated rice yield with NDVI and ASOS data.
\( § \) Est. (9.15): estimated rice yield by the 9.15 sampling method.
the Leave-One-Out cross-validation method) was 0.21 t ha$^{-1}$. The RMSE value between the estimated rice yields using eq. (5) and using the Leave-One-Out cross-validation method was 0.13 t ha$^{-1}$.

$PBIAS$, $RMSE$, and $MAPE$ were used to evaluate the developed model (i.e., eq. (5)) against the observed rice yields. These results of the error evaluation methods are summarized in Table 2. The results showed that the performance of the rice estimation model using both $NDVI$ and monthly precipitation in September (eq. (5)) was higher than that of the model using only $NDVI$ (eq. (6)). However, $MAPE$ in the rice estimation model of eq. (5) was slightly higher than that in the 9.15 sampling method. The largest $PBIAS$ was approximately 0.97% in the 9.15 sampling method, while the largest $RMSE$ (about 0.19 t ha$^{-1}$) and $MAPE$ (about 2.79%) were found in the rice yield estimation model of eq. (6).

Fig. 2 displays the comparison of observed and estimated rice yields (a) and residual rice yields (b). The estimates by the rice yield estimation model of eq. (5) were better than those by eq. (6) and by the 9.15 sampling method in the years 2008 and 2009. Interestingly, the errors of the estimated rice yields by the model using only $NDVI$ (i.e., sim. (VI) in Fig. 2a) were relatively high in those two years when the estimation errors of the 9.15 sampling method were high. Korea Rural Economic Institute (KREI) reported that the errors in the years 2008 and 2009 were because the meteorological conditions after the sampling time was not properly reflected in the 9.15 sampling method (KREI, 2011a; 2011b).

In the year 2007, the model of eq. (6) overestimated rice yield as much as 0.44 t ha$^{-1}$. However, the difference between the observed and estimated rice yields was only 0.12 t ha$^{-1}$ in the model of eq. (5). These results can be explained by considering the monthly precipitation anomaly in the year 2007 (Fig. 4a). Since the monthly precipitation anomaly in September has negative correlation with rice yield, it is likely that the positive value (approximately 240.9 mm month$^{-1}$) of the monthly precipitation anomaly in the year 2007 can offset the errors in the model using only $NDVI$. Typhoon Nari mainly contributed to this large positive monthly precipitation anomaly in the year 2007 (KREI, 2011b). Hayes and Decker (1996) reported that the poor estima-

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**Fig. 2.** Estimated and observed rice yields (a) and residual rice yields (b). Obs. yield: observed rice yield, Sim. (VI): estimated rice yield with only $NDVI$, Sim. (VI, ASOS): estimated rice yield with $NDVI$ and ASOS data, and Est. (9.15): estimated rice yield by the 9.15 sampling method.
tion due to weather variability can be made in this pre-harvest yield estimation method. These results imply that the meteorological conditions after the time of rice yield estimation can improve the performance of the rice yield estimation models.

3.2 Application of the APCC MME hindcasts

As shown in Fig. 3, the range of the correlation coefficients between observed and predicted precipitation were between 0.29 and 0.54 with the eight large-scale atmospheric predictor variables (i.e., SLP, T2M, T850, U200, U850, V200, V850, and Z500). We selected the large-scale atmospheric predictor variables to predict station-scale meteorological predictand variables (i.e., monthly precipitation anomalies for this study) with the highest correlation.

![Fig. 3. Correlation coefficients between observed and predicted precipitation in September. Pearson: Pearson correlation coefficient, and Spearman: Spearman correlation coefficient.](image)

![Fig. 4. The first coupled pattern between (a) U200 (200hPa zonal wind) and (b) precipitation in September. (c) Correlation coefficient between the respective amplitude time series of these patterns.](image)
coefficients. The highest correlation coefficient between the observed and predicted monthly precipitation in September was found, when U200 was used as the large-scale atmospheric predictor variable for the prediction (Fig. 3). The correlation coefficient between the observed and the monthly precipitation hindcasts over the study region increased from 0.35 to 0.54 after the statistical downscaling method was applied.

Fig. 4 shows spatial patterns for the first SVD mode using U200 (a) and station precipitation in September (b) and the time series of expansion coefficients corresponding to the first SVD mode for U200 and precipitation (c). As shown in Fig. 4 (c), the correlation coefficient between the expansion coefficients is 0.91 for the leading SVD mode and this mode accounts for 23.6% of total covariance. The U200 pattern (Fig. 4a) shows changes in an upper level jet pattern and a north-south oriented pattern around the Korean peninsula. Several positive centers of U200 were found over China (about 80E-100E) and over east of Japan (about 150E) and positive anomalies were found over the Korean peninsula (Fig. 4b).

The monthly precipitation anomalies were averaged over all stations for the period of 2002 to 2010 and are depicted in Fig. 5. The observed (Fig. 5a) and predicted (Fig. 5b) monthly precipitation anomalies have the same sign with slightly different magnitudes except for that in 2003. However, these anomalies were not appropriate for replacing the observed monthly precipitation in September in the rice yield estimation model of (eq. (5)). To replace the observed monthly precipitation in September, we added these anomalies to climatology defined as the long-term average of a given variable (for this study, the average monthly precipitation in September between 1983 and 2013). This approach has been widely used because it is very simple and has an effect of bias-correction (Reynolds et al., 1998; White and Toumi, 2013; Xu and Yang, 2012).

These predicted monthly precipitation values in September were applied for (eq. (5)) to timely provide the rice yield estimates for the effective intervention plans in the rice market. For the study period (2002 to 2010), PBIAS, RMSE, and MAPE in the model using the predicted monthly precipitation instead of the observed monthly precipitation in September were 0.42%, 0.24 t ha⁻¹, and 4.35%, respectively. These values were similar to those in eq. (6) (Table 2). While PBIAS was lower than that in the 9.15 sampling method, MAPE was higher than that in the 9.15 sampling. Those estimation errors for eq. (5) using the predicted monthly precipitation in September were consistently higher than those in eq. (5) using the observed monthly precipitation in September. The enhancement of prediction skills of MME seasonal prediction for the period including September can obviously reduce these estimation errors in the case using the predicted monthly precipitation in September. It is suggested that the MME prediction skills for the period should be improved to increase the effectiveness of the rice yield estimation model using predicted meteorological variables.

However, MAPE from 2008 to 2009 when the 9.15 sampling method largely underestimated was 2.38%. This value was lower than that (4.80%) in the 9.15 sampling method or that (3.74%) in the model of (eq. (6)) for those two years. This result implies that the proposed model with the APCC MME seasonal forecasts can be useful to estimate rice yields in the end of August (i.e., earlier than the 9.15 sampling method). To more accurately estimate the rice yields using the proposed approach (i.e., using the model of
eq. (5) with the APCC MME seasonal forecasts), it is suggested that both the rice estimation model (eq. (6)) and the MME prediction skills should be improved for more effective intervention plans in the rice market.

4. Conclusions

In this study, we developed the rice yield estimation model using NDVI and the observed meteorological variables and applied the APCC MME hindcasts for the model. Since accurate calculation of the NDVI at the rice paddy field contributes to better estimation of the rice yield through the developed model, a more accurate rice paddy field mask map over the study period is suggested for the improvement of the rice yield estimation model. Through multiple linear regression analysis with stepwise variable selection, monthly precipitation in September among meteorological variables including sunshine hour and maximum and minimum temperatures was selected for the model. This model was evaluated by comparing with the observed rice yields, the estimated rice yields, and the rice yield estimation model using only NDVI and the 9.15 sampling method. The performance of rice yield estimation model using both NDVI and monthly precipitation in September was better than those of the model using only NDVI and of the 9.15 sampling method. Even though the rice yield estimates applying the APCC MME hindcasts for the rice yield estimation model of eq. (5) were not as good as the 9.15 sampling method from 2002 to 2010, those for the two years (2008 and 2009) when the estimates by the 9.15 sampling method were largely underestimated were better than those by the 9.15 sampling method. This study suggests that the rice yield estimation model and the MME prediction skills should be improved to more accurately estimate and to timely provide rice yields. It is concluded that the proposed approach can be useful to timely provide rice yield estimates that reflect meteorological conditions for the development of more effective intervention plans in the rice market.

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