The comparison of numerous machine learning algorithms performance in classifying rice growth stages based on Sentinel-2 to enhance crop monitoring in national level

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Abstract. The rice monitoring based on Sentinel-2 (SC-S2) has been developed for over nine months. It has been observed as the first and only system which generate rice growth stages maps in 10 m spatial resolution using machine learning in Indonesia. However, the SC-S2 use Support Vector Machine to separate the rice growth stages, which may have poor performances. The objective of this study is to investigate the performance of other classifiers to increase the performance of SC-S2. We used survey data from the field campaign in 2018 and synchronized with Sentinel-2 bands. The model dataset was trained using 61 machine learning algorithms to create 61 rice growth stages models. The models were applied to the Sentinel-2 image of part of Indramayu area. The accuracy, computational time and visual inspection score were collected, and the final score was calculated. The results are the highest final score is Shrinkage Discriminant Analysis, with overall accuracy 88.1% (p<0.001) and the average accuracy of all classifiers is 76.2% (p<0.05). The implication of this study is to propose some changes in the classification process into the SC-S2 for increasing the overall performance, which will provide better information for agricultural policymakers.

1. Introduction
The sustainability of rice production is an important issue for food security, especially in Asia, where rice is a staple food [1]. One of climate change adaptation strategy is to track rice growth stages to forecast rice production. The traditional and common way of collecting data is to submit the rice planting area of a particular area to the Ministry of Agriculture, especially in Indonesia, by local agricultural extension officer every week or month [2]. Manual data collection weakness is speed and spatially inefficient. One solution is using remote sensing based on earth satellite observations to collect the data from space [3]. LAPAN and the Indonesian Ministry of Agriculture launched two MODIS and Landsat-8 rice monitoring systems with 250 and 30-meter resolution, respectively. Both systems can be accessed on http://sipandora.lapan.go.id/site/fasepertumbuhanpadi and http://sig.pertanian.go.id/.

The accuracy of the previous system can be low in some area due to a course/low resolution. One of the solutions is using Sentinel-2 satellites. A newer satellite has been launched since 2010 with a 10-m resolution with two working configurations. It can give 5-days revisited time for global coverage which is equipped with a multispectral sensor that can collect four 10 m bands, six 20 m bands and three 60 m spatial resolution bands [4]. The highest operational level (level 2A) dataset can be downloaded on scihub.copernicus.eu and Google Earth Engine for analyzing the images [5].
The Indonesian Agency for Agricultural Research and Development, Ministry of Agriculture has developed a near-real-time national level of a monitoring system based on rice growth stages based on Sentinel-2 (SC-S2) which can be accessed on http://katam.litbang.pertanian.go.id/sc. The system generates rice growth stages map on the official rice field area from the Ministry of Agriculture (7.4 million ha) automatically using machine learning algorithm/classifier. The advantages of SC-S2 are accurate in 10-m resolution, fast to access, near-real-time with one day lag from the acquisition date. It can also be accessed via an android application (https://play.google.com/store/apps/details?id=com.litbang.googlemapsretrofit). The hardware infrastructure of SC-S2 is four workstations and two servers to generate and provide information from downloading satellite images to providing rice growth stages maps and information in the area.

The SC-S2 used Support Vector Machine (SVM) to separate the rice growth stages which consists of vegetative (0-59 days after sowing (DAS)), reproductive (60 to 90 DAS), ripening (91-120 DSS), flooding and bare land with an overall accuracy of 90.4% [6]. The SVM is one of the machine learning algorithms/classifiers which able to have high accuracy with a small dataset and limited predictors [7-9]. However, SVM analysis is relatively slow, and storage needs rapidly increase with the number of training vectors compared with other classifications [10]. The previous study on detecting rice cropping pattern using radar backscattering temporal profiles shows that the accuracy of SVM is lower than the random forest classifier [11]. Moreover, recent studies have shown that multiple classifiers can be used as a reference to assess performance in each dataset [12], as there is no ideal classifier for any dataset. Moreover, the classifiers in caret package [13] on R statistics language [14] such as decision tree, random forest, discriminant analysis, other classifiers are available to be used and they have not explored for accuracy assessment.

Thus, this study aims to investigate the performance of other classifiers to obtain better classifier options both from the accuracy and computational time perspective. The results of this study can be used to improve the future performance of SC-S2 and to help the fusion algorithm in future rice monitoring to increase the accuracy of rice production or exchange between Asian countries.

2. Model dataset and Sentinel-2 test image

The model dataset contains 426 data points from field campaign on July-September 2018 on Java Island. There are 110 data points for the bare land class, 54 data points for flooding class, 99 for data points for vegetative, 67 reproductive class, and 96 for ripening class. Each data point was collected with GPS handheld and validated with Sentinel-2 images. The model dataset was synchronized with no cloud data of Sentinel-2 images with ten bands as the predictors with formulas as follows:

\[ \text{Rice growth stages} \sim B02 + B03 + B04 + B05 + B06 + B07 + B08 + B11 + B12 + B8A \]

Sentinel-2 test data is a paddy field area in Indramayu regency which the acquisition date is 31 July 2018 with path/row T48MZU. Thus, it was cropped with the official rice field area from the Ministry of Agriculture with total area 131,500 ha or 13,150,000 pixels (10 m x 10 m) as shown in figure 1. The area mostly had a double-cropping pattern with the rice-rice-bare land pattern. Some of the areas can triple rice cultivation but only if there are any subsidized inputs from the government. The planting time of the area depends on the irrigation of Jatiluhur dam irrigation system [15]. However, mostly the area is near the coast, which susceptible to flooding, which makes this area usually have the last water distribution. The first cultivation was on February-March and the second rice cultivation is on July-August.

3. Methods

This paper aims to find the best classifier for the rice monitoring system from the caret package in the R programming language. The first step is to find the accuracy of each classifier to find overall accuracy (OA), producer’s accuracy (PA), and user’s accuracy (UA). The next step is to apply the model to Sentinel-2 test image to check classifying time from the Sentinel-2 image to rice growth stages map and
for manual visual inspection. The last step is to calculate the final score with accuracies divided by computational time. The top six is the best candidate for SVM replacement, as shown in figure 2.

![Figure 1](image1.png)

**Figure 1.** The Sentinel-2 test image on natural colour (Red-Green-Blue)

![Figure 2](image2.png)

**Figure 2.** The workflow of the method

### 3.1. Classifiers and accuracy assessment

The machine learning algorithms that available in the caret package is 238 classifiers. However, we only used 61 classifiers because the other machine learning algorithms are for regression only, and some need more data points or predictors as listed in table 1.

The model dataset was partitioned into 70:30 per cent as training and test dataset, respectively. The partition scheme was chosen to learn data variance and also to accommodate the availability of the number of test data due to the limitation of the field survey data points as some previous studies have been applied the same scheme partition with high accuracy [9]. The training data then train with a classifier with a default parameter. During the training, the grid search was done with cross-correlation using the leave-one-out cross-validation method to ensure unbiased accuracy measurement. The final model with the highest overall accuracy was used to test data independently using a confusion matrix. The matrix calculated the overall accuracy, producer’s accuracy for each class, and user’s accuracy for each class with the formula: overall accuracy is the total correct divided by the total number of data. The
producer’s accuracy is measuring the probability of a reference data being correctly classified and user’s accuracy to measure the probability that data classified on with the model represents that class on the real-world data [17].

3.2. Sentinel-2 rice growth stages map, and visual inspection

The highest model for each classifier was saved and applied to Sentinel-2 test data. The computational time was calculated from the program loading the Sentinel-2 image with ten bands into the memory, load the model classifiers, and masking with the official rice area from the Indonesian Ministry of agriculture which has been agreed with the Indonesian Ministry of Agrarian Affairs and Spatial Planning/National Land Agency. This study used a desktop computer with specification as follows: Windows 10 OS, Processor 3.4 GHz, four cores, eight logical processors, 16 GB RAM, and SATA hard disk. The program run multithreading using six logical processors for building the model and only one thread/one logical processor for classifying the test image.

The generated maps were compared with the Sentinel-2 test image with Enhanced vegetation index (EVI) band, and false colour image (B11-B8-B3) is required as the test data from the field campaign has been used to calculate the accuracy in the previous section (3.1). The EVI is a vegetative index that consists of the red band, blue band, and near infra band can be used to check the consistency of rice growth stages map [18]. The general classification with EVI value was bare land/flooding (EVI<0.3), vegetative/ripening (0.3≤EVI<0.6), reproductive (EVI≥0.6) [19]. Moreover, the false-colour image can be used to separate the flooding phase (dark blue), vegetative (less dark blue), reproductive (dark green), ripening (light green), and bare land (brown). The visual inspection was scored from 0 to 10. The score zero means the classifying process is failed and score ten means the classifiers have been successfully classified the image and mostly concurrent with the hen false-colour map and the EVI map.

3.3. The final score for the candidacy

The final score for the replacement candidacy can be derived from the overall accuracy, five producer’s accuracy, five user’s accuracy, score from visual inspection, the computational time on time spent for building model in minutes, and time spent in classifying in minutes. The formula of the final score as follows:

$$\text{Final score} = \frac{OA + \sum PA + \sum UA + VI}{\text{Computational time}}$$

where OA: overall accuracy, ΣPA: a total of producer’s accuracy, ΣUA: a total of user’s accuracy, VI: the score from visual inspection. The time dimension is in minute(s).

The most possible and highest value of the final score is 22 where the accuracy value is 100% to all classes and an excellent value from visual inspection within the one-minute computational time from the total time of building model and classifying time. The top six of the final score can be proposed to be the replacement of SVM classifiers on SC-S2.

4. Results and discussion

4.1. Accuracy of classifiers

Table 2 shows that the overall accuracy from the top 30 of the final score is varying from 41-95% with 127 points of test data. The qda, loclda, rda, regLogistic, and bagFDAGCV is the top five of classifier of overall accuracy and the lowest in the plr. The overall accuracy assessment shows that bare land and flooding has good accuracy for both PA and UA than rice growth stages (vegetative, reproductive, and ripening). Sun, Fang, Liu and Ye [20] reported that soil on the bare land has different spectral profiles
than rice growth stages as the reflectance is low wavelength on 800 to 1000 nm. On the flooding class, the spectral profile is reflectance value is low on 800 nm, which differ from the bare land class.

Table 1. The list of classifiers used in this study [16]

| No. | Classifiers   | Full name                                      | No. | Classifiers   | Full name                               |
|-----|---------------|------------------------------------------------|-----|---------------|-----------------------------------------|
| 1   | avNNet        | Model Averaged Neural Network                  | 32  | ownn          | Optimal Weighted Nearest Neighbor Classifier |
| 2   | bagFDA        | Bagged Flexible Discriminant (FDA) Analysis    | 33  | parRF         | Parallel Random Forest                  |
| 3   | bagFDAGCV     | Bagged FDA using generalized cross-validation (gCV) Pruning | 34  | partDSA       | Deletion/ Substitution/ Addition Algorithm for Partitioning the Covariate Space in Prediction |
| 4   | bayesglm      | Bayesian Generalized Linear Model              | 35  | pda           | Penalized Discriminant Analysis         |
| 5   | BstLm         | Boosted Linear Model                           | 36  | Penalized LDA | Penalized Linear Discriminant Analysis |
| 6   | bstSm         | Boosted Smoothing Spline                       | 37  | plr           | Penalized Logistic Regression           |
| 7   | bstTree       | Boosted Tree                                   | 38  | polr          | Ordered Logistic                        |
| 8   | C5.0          | C5.0                                           | 39  | qda           | Quadratic Discriminant Analysis         |
| 9   | C5.0Rules     | Single C5.0 Ruleset                            | 40  | rda           | Regularized Discriminant Analysis       |
| 10  | C5.0Tree      | Single C5.0 Tree                               | 41  | regLogisti c  | Regularized Logistic Regression         |
| 11  | cforest       | Conditional Inference Random Forest            | 42  | rf            | Random Forest                           |
| 12  | ctree         | Conditional Inference Tree                     | 43  | RFlda         | Factor-Based Linear Discriminant Analysis |
| 13  | ctree2        | Conditional Inference Tree 2                   | 44  | rpart         | Recursive Partitioning (RP) and Regression Trees (RT) 1 |
| 14  | dnn           | Stacked AutoEncoder Deep Neural Network        | 45  | rpart1SE      | RP and RT one-standard-error            |
| 15  | gam           | Generalized Additive Model using Splines       | 46  | rpart2        | RP and RT 2                             |
| 16  | gamLoess      | Generalized Additive Model using locally weighted running line smoother (LOESS) | 47  | rpartScore    | Recursive Partitioning and Regression Trees Score |
| 17  | gcvEarth      | Multivariate Adaptive Regression Splines       | 48  | RSimca        | Robust Soft Independent Modelling of Class Analogies (SIMCA) |
| 18  | kknn          | k-Nearest Neighbors                            | 49  | sda           | Shrinkage Discriminant Analysis         |
| 19  | knn           | k-Nearest Neighbors 2                          | 50  | snn           | Stabilized Nearest Neighbor Classifier  |
The low number of classifiers that have high accuracy on vegetative and ripening is the spectral profile is almost the same except 700 to 900 nm wavelength [20]. The ripening is higher than the vegetative. The same problem with rice growth stages problem with vegetation indices which depend on NIR and red band to separate vegetative and ripening stage as they have the same range value except the ripening stage has a peak of value before [21]. On the other hand, the reproductive class has a distinct spectral profile from other rice growth stage since it has the highest value on 700 to 900 nm.

The overall classifier accuracy in this study mostly depends on the bare land and flooding class. Importantly, vegetative and ripening are varied. The classifier may have better accuracy if the fusion algorithm could be applied as the result of Minh, Avtar, Mohan, Misra and Kurasaki [22] using a radar-based sensor. They used Sentinel-1 data to create rice phenology with backscattering of vertical-horizontal (VH) in decibel (dB). The vegetative will gives lower backscattering value due to low double scattering, and reproductive and ripening have higher backscattering value due to volume and double scattering with the rice plant.

4.2. The computational time and visual inspection

The computational time that has been tracked shows that top of 30 of the classifiers spent less than four minutes for building the model and less eight minutes for applying the model, as shown in table 2. \textit{regLogistic}, \textit{lvq}, \textit{sda} is the fastest classifier for classifying the model (<2.2 minutes). The results show that the standard classifiers which usually used in remote sensing classification such as SVM, neural network, and random forests are not the best time for classifying in R programming language due to...
higher complexity of the algorithm. The model dataset is only 299 points which may over-redundancy the classifiers to find the best parameter [23].

Table 2. The accuracy assessment of top 30 from 61 classifiers for OA, total accuracy, time spent to build the model, time spent to classify the image, visual score, and final score.

| No | Classifiers | OA | PA (BL, FL, VEG, REP, RIP) | UA (BL, FL, VEG, REP, RIP) | Tot. Acc. | Build time | Apply time | Visual score | Final Score |
|----|-------------|----|-----------------------------|-----------------------------|-----------|------------|------------|--------------|-------------|
| 1  | sda         | 88 | (97,100,61,92,79)           | (97,84,79,89,83)            | 951       | 0.04       | 2.12       | 10           | 9.1         |
| 2  | hvq         | 84 | (97,100,78,81,58)           | (97,100,74,85,55)           | 912       | 0.08       | 2.03       | 9            | 8.6         |
| 3  | pda         | 87 | (97,100,61,92,74)           | (97,84,79,87,82)            | 941       | 0.04       | 2.29       | 10           | 8.4         |
| 4  | lda         | 87 | (97,100,61,92,74)           | (97,84,79,87,82)            | 941       | 0.02       | 2.36       | 10           | 8.1         |
| 5  | lda2        | 87 | (97,100,61,92,74)           | (97,84,79,87,82)            | 941       | 0.03       | 2.41       | 10           | 8.0         |
| 6  | svmLinear2  | 87 | (97,100,78,86,68)           | (97,100,78,84,72)           | 949       | 0.05       | 3.21       | 9            | 5.7         |
| 7  | rpart1SE    | 82 | (94,100,67,69,79)           | (100,100,71,86,52)          | 905       | 0.03       | 3.38       | 10           | 5.6         |
| 8  | svmLinear   | 90 | (97,100,83,89,74)           | (97,100,79,86,82)           | 977       | 0.06       | 3.63       | 10           | 5.4         |
| 9  | qda         | 92 | (97,100,83,89,89)           | (97,100,75,97,85)           | 1,003     | 0.02       | 2.78       | 4            | 5.0         |
| 10 | ctree       | 84 | (97,100,83,81,53)           | (100,100,71,85,53)          | 912       | 0.07       | 3.70       | 9            | 4.8         |
| 11 | gcvEarth    | 91 | (94,100,83,86,89)           | (94,100,79,94,81)           | 991       | 0.09       | 3.63       | 6            | 4.3         |
| 12 | PenalizedLDA| 81 | (97,100,61,72,68)           | (100,84,85,81,52)           | 888       | 0.04       | 4.45       | 10           | 4.2         |
| 13 | rf          | 85 | (97,100,89,69,74)           | (97,100,70,89,64)           | 938       | 0.30       | 4.66       | 10           | 3.9         |
| 14 | rpart2      | 75 | (94,100,0,75,84)            | (100,100,0,79,39)           | 751       | 0.02       | 3.45       | 6            | 3.9         |
| 15 | parRF       | 85 | (94,100,89,69,79)           | (97,100,73,89,63)           | 942       | 0.31       | 4.84       | 9            | 3.6         |
| 16 | naive       | 83 | (94,100,78,72,74)           | (97,95,82,87,54)            | 919       | 0.06       | 4.31       | 6            | 3.5         |
| 17 | multinom    | 87 | (94,100,72,78,95)           | (94,100,68,97,72)           | 960       | 0.17       | 3.81       | 4            | 3.4         |
| 18 | ctree2      | 82 | (97,100,83,100,0)           | (100,100,71,68,0)           | 799       | 0.13       | 3.67       | 5            | 3.4         |
| 19 | knn         | 85 | (97,100,72,81,68)           | (97,95,87,83,59)            | 927       | 0.02       | 5.87       | 10           | 3.3         |
| 20 | svmLinear3  | 89 | (97,100,50,94,89)           | (94,88,75,89,89)            | 955       | 2.64       | 2.12       | 6            | 3.3         |
| 21 | Linda       | 84 | (91,100,44,92,79)           | (100,78,62,92,71)           | 896       | 0.22       | 3.82       | 4            | 3.2         |
| 22 | spls        | 84 | (97,100,33,94,74)           | (94,81,86,79,82)            | 906       | 0.62       | 3.67       | 4            | 3.0         |
| 23 | mda         | 88 | (91,100,78,83,89)           | (100,100,74,91,71)          | 968       | 0.12       | 4.50       | 4            | 3.0         |
| 24 | rpart       | 69 | (94,100,0,100,0)            | (100,100,0,48,0)            | 608       | 0.03       | 3.47       | 3            | 2.6         |
| 25 | plr         | 41 | (94,100,0,0,0)              | (94,22,0,0,0)               | 351       | 0.75       | 2.24       | 4            | 2.5         |
| 26 | svmPoly     | 87 | (94,100,78,86,74)           | (97,100,82,86,67)           | 953       | 0.60       | 7.39       | 10           | 2.4         |
| 27 | treebag     | 85 | (94,100,83,69,84)           | (100,100,75,96,55)          | 946       | 0.13       | 7.09       | 8            | 2.4         |
| 28 | rpartScore  | 69 | (94,100,100,0)              | (100,58,0,60,0)             | 581       | 0.63       | 3.40       | 3            | 2.2         |
| 29 | mnet        | 64 | (94,100,81,0)               | (94,33,0,94,0)              | 562       | 0.31       | 3.79       | 3            | 2.1         |
| 30 | monmlp      | 87 | (94,95,72,83,84)            | (97,100,62,86,84)           | 944       | 3.92       | 3.24       | 4            | 1.9         |

Note: PA: Producer’s accuracy, UA: User’s accuracy, BL: Bare land, FL: Flooding, VEG: Vegetative, REP: Reproductive, RIP: Ripening, Tot. Acc.: Total accuracy, Build time: Building the model time in minutes, and Apply time: Applying the model time in minutes. The complete list can be downloaded on https://github.com/FadhullrahRamadhani/Comparison-of-performance-of-rice-growth-stages-classifiers

The SVM Radial which used by SC-S2 got the perfect score of the visual inspection like other 12 classifiers from decision tree, random forest, SVM, and discriminant analysis characteristics group. Those classifiers can classify five class with the right consistency and uniform as the same as previous
studies [12,24,25]. The main advantages of the decision tree as reported by Pal and Mather [25] that it is fast and no statistically assumption. The random forest which the development of the decision tree has gained a nonparametric statistical model and can predict the importance of predictors [26]. On the other hand, SVM has capabilities to classify from a limited dataset with reasonable accuracy [7,8]. The discriminant analysis also has an advantage which is fast due to dimensional reducibility [27]. The idea to compare the classifier is to upgrade the SC-S2 from a static model into a dynamic and interactive system where the user can adjust the accuracy based on pre-trained data and the new data from ground truth without any modifications from the primary classification system in SC-S2 using Google Earth Engine (GEE). The GEE has been the capability to classify the satellite images with supervised classification with random forest, SVM and decision tree which connect with TensorFlow models [28]. Importantly, this result of this study and GEE capability may enhance the user experience to use SC-S2.

4.3. The final score and the final candidates

Table 2 shows the final score based on accuracy assessments, computational time, and visual inspection. The average score is 2.53, with the highest score is shrinkage discriminant analysis (sda) with 9.06. The sda got the best score because of its accuracy over 70% except for vegetative class on producer’s accuracy due to misclassifying with flooding class. Moreover, the sda also the fastest time for building the model with only 2.28 seconds and classifying the image with 2.12 minutes. The comparison with the existing classifier for SC-S2, which SVM Radial is 5.63 seconds and 13.3 minutes, respectively. Importantly, the visual inspection shows that sda maps and SVM Radial maps have the same score, which shows the high consistency with manual inspection. It means there is an opportunity to increase the speed and accuracy with sda classifiers without losing accuracy for 627%. The same result also reached by Pang, Tong and Zhao [29]. They found that sda algorithm could decrease the mean misclassification 28% compare with SVM. They also suggested that sda can deal with a small dataset with high dimensional data due to the feature selection algorithm with high efficiency [30].

Surprisingly, the final candidacies for the classifier replacement on SC-S2 are sda, lvq, pda, lda, lda2, and svmLinear2. Figure 3 shows the rice growth stages map from six top classifiers. It indicates that lvq and svmLinear2 have collective visual conformity and have some differences with sda, lvq, pda, lda, lda2, especially with flooding class. Mostly, the classifiers are from the discriminant analysis characteristic group (sda, pda, lda and lda2), which shows some new alternatives for using the discriminant analysis on remote sensing area. The processing time for top six classifiers also under three minutes which indicate the high efficiency on the algorithm. Lim, Loh and Shih [31] reported that discriminant analysis was indeed faster than SVM, which consistent with this study. Another unexpected result is the lvq as the second runner up. The lvq is a has been used to predict rice-planted area with RADARSAT [32] with good result. However, other researcher stated that lvq had a mediocre accuracy in determining oil spill using a Synthetic Aperture Radar satellite sensor [33].

Therefore, there might be a change that the accuracy of the classifier can be worse, with more data points come to the validation mechanism. The result of the final candidacies needs to be checked with spatial-temporal accuracy in the ground truth, and the classifiers can be tuned up by changing the parameters [34]. Moreover, the advances of fusion technique and free satellite images in cloud computing make possible to develop an interactive and dynamic mapping where the user can choose the source of the satellite images, and pre-trained data are available to classify the images with the capability to increase the number of the training dataset from user’s ground truth data which inspired from previous works [24].
Figure 3. The Sentinel-2 test image on 31 July 2018 for (a) false colour map, (b) EVI map, and the rice growth stages map based on (c) sda, (d) lvq, (e) pda, (f) lda, (g) lda2 and (h) svmLinear2 classifiers.
5. Conclusion
Even though SC-S2 has been operational over ten months in near-real-time, the correction and improvement need to be investigated to increase the accuracy and operational time. One of the steps is to find another classifier to be fitted on SC-S2. This study found that sda, lvq, pda, lda, lda2 and svmLinear2 are good candidates due to their high accuracy, fast, and a perfect score of visual inspection. The rice growth stages maps can be downloaded https://github.com/FadhlullahRamadhani/Comparison-of-performance-of-rice-growth-stages-classifiers to be explored. However, this study has some limitations as follows: the classifiers only tested on R programming language, each classifier was not optimized by changing its kernel, and limited data points in a certain area which may not represent some small area rice paddy field in a swamp area, and hilly area.

Further research needs to be investigated the performance of fusion predictors with different spatial resolutions to overcome cloudy area in tropical countries. Moreover, the consistency of overtime needs to be fact-checked seamlessly into the application. The output of this study and SC-S2 can be expanded into another classification problem in agriculture using a satellite-based sensor such as determining vegetative condition are in the dry land, or dynamic cropping calendar. Moreover, there is a possibility to integrate the result with low-level radar-based satellite sensor or using a drone to capture certain area for determining crop production, crop productivity, and crop inputs such as fertilizer and insurance risk. The accurate information coupled with fast analysing time and low operational cost is the key for a better policy for stakeholders to maintain food security.

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