Evaluating the 2019 NARO-APCC Joint Crop Forecasting Service Yield Forecasts for Northern Hemisphere Countries

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ABSTRACT: Forecasting global food production is of growing importance in the context of globalizing food supply chains and observed increases in the frequency of climate extremes. The National Agriculture and Food Research Organization–Asia-Pacific Economic Cooperation Climate Center (NARO-APCC) Crop Forecasting Service provides yield forecasts for global cropland on a monthly basis using seasonal temperature and precipitation forecasts as the main inputs, and 1 year of testing the operation of the service was recently completed. Here we evaluate the forecasts for the 2019 yields of major commodity crops by comparing with the reported yields and forecasts from the European Commission's Joint Research Centre (JRC) and the U.S. Department of Agriculture (USDA). Forecasts for maize, wheat, soybean, and rice were evaluated for 20 countries located in the Northern Hemisphere, including 39 crop-producing states in the United States, for which 2019 reported yields were already publicly available. The NARO-APCC forecasts are available several months earlier than the JRC and USDA forecasts. The skill of the NARO-APCC forecasts was good in absolute terms, but the forecast errors in the NARO-APCC forecasts were almost always larger than those of the JRC and USDA forecasts. The forecast errors in the JRC and USDA forecasts decreased as the harvest approached, whereas those in the NARO-APCC forecasts were rather stable over the season, with some exceptions. Although this feature seems to be a disadvantage, it may turn into an advantage if skillful forecasts are achievable in the earlier stages of a season. We conclude by discussing relative advantages and disadvantages and potential ways to improve global yield forecasting.

KEYWORDS: Climate prediction; Regression analysis; Forecast verification/skill; Seasonal forecasting; Agriculture; Climate services

1. Introduction

The globalization of the economy has changed food supply chains worldwide. Consumers in many countries increasingly rely on food imports (FAO 2011). In addition to domestic production, governmental and commercial entities in import-dependent countries pay close attention to food production and export prices in the major food-exporting countries (Iizumi et al. 2013). Climate extremes during the growing season are key drivers of the recent rise in global hunger and one of the leading causes of severe food crises (FAO 2018). Therefore, in the face of the food crises that occurred during the last two decades and the observed increases in the frequency of climate extremes, monitoring and forecasting global food production are of growing importance (Iizumi and Kim 2019). This is further exemplified by initiatives such as the G20 Agricultural Market Information System (AMIS) and the Group of Earth Observations Global Agricultural Monitoring (GEOGLAM; see Becker-Reshef et al. 2019).

Since April 2017, the National Agriculture and Food Research Organization (NARO) and the Asia-Pacific Economic Cooperation (APEC) Climate Center (APCC) have jointly been developing a global crop forecasting system. The statistical yield models used in the system utilize the APCC multimodel ensemble (MME) of seasonal temperature and precipitation forecasts (Min et al. 2014; Sohn et al. 2019) as the input to predict changes in crop yields in the coming harvesting year relative to the previous year's yield (Iizumi et al. 2018b). Using the system, the NARO-APCC Joint Crop Forecasting Service provides yield anomaly predictions every month for crops and countries where harvesting normally occurs within three to six months of the release of forecast information (Iizumi 2020). The development status of and plan for the service were presented to the representatives of over 20 countries and international organizations at the 16th Session of the AMIS Global Food Market Information Group held in October 2019 in Rio de Janeiro (AMIS 2019). Four major crops, including maize, rice, wheat, and soybean, are considered by the service. Currently, the service is in its test operation phase lasting from June 2019 to March 2021.

As one year of the test operation of the service was just recently completed (Table S1 in the online supplemental material), an

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evaluation of the NARO-APCC forecasts is appropriate to understand the current status of the global crop forecasting and the scientific and technical barriers that need to be addressed in future research. This study aims to assess the skills of the NARO-APCC forecasts for the 2019 season in Europe (17 countries), the United States, Japan, and South Korea located in the Northern Hemisphere. The official 2019 yield statistics for the countries are already publicly available. This study also compares forecasts for the European Union (EU) countries produced by the JRC and those for the United States released by the USDA with the NARO-APCC forecasts to highlight relative advantages and disadvantages. The NARO-APCC forecasts are solely based on seasonal climate forecasts, whereas the JRC forecasts incorporate other sources of information, including historical yield trends, weather observations, satellite remote sensing, outputs from a process-based crop model, as well as the 10-day ECMWF forecast. By contrast, the USDA forecasts heavily rely on field surveys. Therefore, a comparison of the NARO-APCC forecasts with the JRC and USDA forecasts is expected to point to the benefits and limitations of using seasonal climate forecasts in predicting variations of crop yields. Finally, we discussed potential ways to further improve global crop forecasting.

2. Material and methods

a. *Reported yields*

National annual yield statistics for the 17 EU countries and Serbia for the period 2016–19 were obtained from Eurostat (https://ec.europa.eu/eurostat/data/database). Serbia is not an EU member country. The list of countries considered in this study is available in Table S2. Crop-country combinations with an average annual national production $>$ 1 million tons (Mt) over the 2015–17 period, calculated based on the FAO statistical database, were analyzed. There was a difference in the time period (2016–19 versus 2015–17) because FAO data for 2019 were not yet available when this study was conducted. Rice and soybean are relatively minor crops in Europe, and only Italy within the EU produces $>$1 Mt of these crops. For the 2019 season in Italy, rice yield statistics were available from Eurostat, while soybean yield statistics had not been reported when we conducted this study. For this reason, maize, wheat, and rice were studied in Europe.

Annual yield statistics for the United States at national and state levels for the period 2016–19 were collected from the USDA's National Agricultural Statistics Service (NASS) Quick Stats (https://quickstats.nass.usda.gov/). The 39 major producing states for these crops were considered (Table S3). The data collected from the NASS were originally recorded in bushels per acre for maize, soybean, and wheat and in pounds per acre for rice, and these values were converted into tons per hectare before the analysis. Maize, soybean, rice, and total wheat (a crop category that combines winter wheat, durum wheat and other spring wheat) were analyzed for the United States. Although separate yield statistics are available for the individual wheat types, total wheat was selected to provide a consistent comparison with the NARO-APCC forecasts.

Rice is a relatively minor crop in the United States and Europe compared to maize and wheat, with some exceptional rice-producing states and counties. Therefore, national rice yield statistics from Japan and South Korea for the period 2016–19 were collected from the Ministry of Agriculture, Forestry, and Fisheries of Japan and Statistics Korea's Korean Statistical Information Service, respectively.

b. *Yield forecasts*

1) JRC FORECASTS

The JRC has provided yield forecasts for major crops in EU countries as well as neighboring countries since 1993 using the MARS-Crop Yield Forecasting System (MCYFS, see MARSWiki 2020; Bussay et al. 2015; van der Velde et al. 2018). The JRC national 2019 yield forecasts for the EU countries were obtained from the MARS Bulletins Archive (https://ec.europa.eu/jrc/en/mars/bulletins). JRC yield forecasts are available for soft (mostly winter) and durum (mostly spring) wheat. These forecasts were combined into total wheat yield forecasts through area-weighting for the analysis. The number of EU countries analyzed in this study varied by crop and ranged from one country for rice to 12 countries for wheat (Table S2). The JRC forecast for wheat in Latvia was available, but the reported yield was not available. Thus, this crop–country combination was discarded from the analysis.

The MCYFS facilitates crop monitoring, agro-meteorological and statistical analyses, and yield forecasting at the country level (Genovese and Bettio 2004). The JRC yield forecasts are provided on a monthly basis by combining information from multiple sources, such as historical yield trends, weather observations and forecasts, as well as process-based crop model outputs, satellite remote sensing, and expert knowledge. Auxiliary information from news sources and agricultural organizations is also considered by JRC analysts. Analysts use statistical methods to make yield forecasts. Predictors aggregated at the national level are based on Europe-wide gridded weather observations and forecasts (currently at 25 km), gridded agro-meteorological indicators, gridded satellite-derived vegetation indices, and gridded crop model outputs, all with a 10-day time step. Gridded weather observations and 10-day weather forecasts drive the World Food Studies (WOFOST) crop model, which simulates crop development stages, water-limited biomass, storage organ yield, leaf area index and transpiration, total water consumption and root-zone soil moisture (Ceglar et al. 2019; de Wit et al. 2019). The gridded data are aggregated at the lowest level of administrative unit by weighting with the arable land area in each 25-km grid cell derived from non-crop-specific land cover maps (CORINE; see Feranec et al. 2010). The reported crop area in each administrative unit is used for aggregation from the lowest administrative level (NUTS 3; with NUTS referring to Nomenclature of Territorial Units for Statistics) to the national level. The resulting predictors are used as input to build the statistical models that explain the variability in the time series of reported national yield statistics obtained from Eurostat. The statistical methods used to forecast the national yields are trend analysis, regression analysis, and similarity analysis based on principal component analysis and cluster analysis.

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2) USDA FORECASTS

Yield forecasts for the United States at the national and state levels for the 2019 season were collected from NASS Quick Stats. For the United States, the USDA yield forecasts for maize, soybean, and rice at the national and state levels are available from mid- to late season (August, September, October, and November). The USDA forecasts begin in May for winter wheat and in July for spring wheat. The final yield forecasts are released in August for both winter and spring wheat. The USDA national-level total wheat forecasts (harvested area of winter and spring wheat are considered in the calculation of total wheat forecasts as the weighting factor) become available in July and August and were used for comparison against the NARO-APCC forecasts.

The USDA yield forecasts provided by the NASS are essentially based on surveys (Vogel and Bange 1999; FAO 2016). The USDA yield forecasts are provided at the county level by combining the results of two surveys using statistical models. Statistical models are used to predict the final number of fruits and the final weight per fruit from observable crop conditions (Vogel and Bange 1999). The first surveys are the agricultural yield surveys, in which producer-reported data, including area planted, area to be harvested, and expected yields, are collected on a monthly basis. Data on small grain crops, including winter wheat, durum wheat, and other spring wheat, are collected from May through August, while those on row crops, such as maize, soybean, and rice, are collected from August through November. The second surveys are the objective yield surveys, which conduct objective measurements at sampled farm fields and include winter wheat, maize, and soybeans (rice is not included). Objective yield surveys are costly and thus conducted only in the top producing states. County-level yield forecasts are aggregated at the state and national levels based on crop acreage collected from agricultural yield surveys and quarterly agricultural surveys.

The impacts of weather on crop growth and expected yield are considered through the surveys. The USDA yield forecasts assume normal weather conditions for the remainder of the growing season. If weather, disease, insects, or other conditions change substantially from the expected normal, then the final estimate may differ significantly from the earlier forecasts (Schnepf 2017). Neither weather and climate forecasts nor a combination of crop models and satellite remote sensing is used within the nationwide yield forecasting system in the United States, although nonofficial yield forecasts at the state level utilize crop models and climate forecasts (FAO 2016). Satellite-based yield and area estimates are also provided by the NASS and are released after the harvest, but these are not used in the USDA yield forecasts made and released during the season. More details on the USDA yield forecasting method are available in Vogel and Bange (1999), Egelkraut et al. (2003), FAO (2016), and Schnepf (2017).

3) NARO-APCC FORECASTS

We used yield anomaly forecasts at the national level provided by the NARO-APCC Joint Crop Forecasting Service from June 2019 to April 2020, which covered most of the 2019 season in the Northern Hemisphere. During the test phase, the NARO-APCC forecasts have been shared with interested parties around the world. The multiple regression models used in the service associate key growing season temperature and precipitation anomalies with yield anomalies and were calibrated from one 1.125° grid cell to another based on the representation of actual yield (the Global Dataset of Historical Yields version 1.1; Iizumi et al. 2014; Iizumi and Ramankutty 2016) and the actual climate conditions [the Japanese 25-year Reanalysis (JRA-25); Onogi et al. (2007)] for the 1984–2010 period, as elaborated in Iizumi et al. (2018b). The APCC MME temperature and precipitation forecasts issued on the 25th of every month (20th of every month after November 2019) are input to the models to derive yield anomaly forecasts within 17 days from the issued climate forecasts (Table S1). The aggregation of yield anomaly forecasts from the grid-cell level to the country level was carried out for the crop-specific harvested area in 2000 (Monfreda et al. 2008) as weights. Currently, no information derived from satellite remote sensing, weather observations, or crop models is used within the NARO-APCC forecasts.

The predicted variable of the JRC and USDA forecasts analyzed in this study is the yield in tons per hectare, while that of the NARO-APCC forecasts is the yield anomaly as a percentage of the normal yield. Because of this inconsistency, postprocessing was performed on the NARO-APCC forecasts. As described in Iizumi et al. (2018b), the yield anomaly used in the NARO-APCC forecasts is defined as

$$\Delta Y_t = \frac{Y_t - Y_{t-1}}{\overline{Y_{t-3:t-1}}} \times 100, \tag{1}$$

where the subscript t indicates the harvesting year; ΔY is the yield anomaly (% of the normal yield); Y_t and Y_{t-1} are the yields in the coming harvesting year and the previous year (t ha^{-1}), respectively; and $\overline{Y_{t-3:t-1}}$ is the 3-yr average yield for the period from year $t-3$ to $t-1$. Accordingly, the yield anomaly forecast can be converted into the yield forecast by

$$Y_t^{f,\text{NARO-APCC}} = \frac{\Delta Y_t^f \overline{Y_{t-3:t-1}^r}}{100} + Y_{t-1}^r, \tag{2}$$

where the superscripts f and r indicate the forecast and reported data, respectively. The variable $Y^{f,\text{NARO-APCC}}$ is the NARO-APCC yield forecast (t ha^{-1}) derived by combining the yield anomaly forecast (ΔY^f, percent of the normal yield) with the reported yields for the 3 years from $t-3$ to $t-1$ ($\overline{Y^r}$, t ha^{-1}). For the 2019 yield forecasts, the data reported for the 2016–18 period were used. The NARO-APCC yield forecasts derived in this manner are analyzed hereafter. In general, the final goal of organizations that maintain operational crop forecasting services is to provide production forecasts to inform policymakers and markets about supply, and yield forecasts are part of these production forecasts. Therefore, evaluating yield forecasts rather than yield anomaly forecasts is of primary interest for experts involved in operational crop forecasting

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services. In addition, while winter wheat and spring wheat are separately predicted within the NARO-APCC system, these were aggregated to a total wheat forecast for the analysis, mainly because yield forecast users, such as governmental agencies, are often more interested in aggregated category of a crop than subcategories.

4) Simple forecasts

We also used a simple forecasting method to provide ''reference'' yield forecasts. In the method adopted here, the 3-yr average reported yield for the period from $t-3$ to $t-1$ represents the forecasted yield for the coming harvesting year t ($Y^{f,\mathrm{Simple}}$, t ha^{-1}):

$$Y_t^{f,\mathrm{Simple}} = \overline{Y_{t-3:t-1}^r}. \tag{3}$$

This method is solely based on reported yields, and no additional information derived from producer surveys, field measurements, weather observations, climate forecasts, satellite remote sensing, or crop models is considered. The forecasts derived from the simple method provide a benchmark to measure the added value of the JRC, USDA, and NARO-APCC forecasts that consider additional sources of information. The method is conceptually similar to the extrapolation of historical yield trends in predicting yield. Although 3-yr average yields may be conservative or even pessimistic yield forecasts compared to extrapolated yield trends when yields keep rapidly increasing, they serve as reasonable forecasts when yields are slowly increasing or stagnating (Grassini et al. 2013; Iizumi et al. 2018a). Utilizing simple method-based forecasts as the reference for assessing improvements achieved by using more sophisticated methods is a common practice in intercomparison and is seen, for instance, in Lecerf et al. (2019).

c. Skill scores

We utilized Pearson's correlation coefficient, the root-mean-squared error (RMSE), the absolute error (AE), and the absolute percentage error (APE) to measure the skill of the yield forecasts. The correlation coefficient (R; dimensionless) is computed as

$$R = \frac{\sum_{i=1}^{n}(Y_{2019,i}^r - \overline{Y_{2019}^r})(Y_{2019,i}^f - \overline{Y_{2019}^f})}{\sqrt{\sum_{i=1}^{n}(Y_{2019,i}^r - \overline{Y_{2019}^r})^2}\sqrt{\sum_{i=1}^{n}(Y_{2019,i}^f - \overline{Y_{2019}^f})^2}}, \tag{4}$$

where the subscript i is the country (or state for the United States) and n is the number of countries (or states) within an administrative unit of interest (Europe or the United States). The root-mean-squared error (RMSE; t ha^{-1}) is computed as

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{2019,i}^f - Y_{2019,i}^r\right)^2}{n}}. \tag{5}$$

As seen in Eqs. (4) and (5), these equations compare the reported and forecasted 2019 country (or state) yields within an administrative unit. The correlation and RMSE values were calculated for maize and wheat in the EU and for maize, soybean, and rice in the United States, where multiple samples were available for 2019. When only a limited number of samples were available (this was the case for wheat in the United States and for rice in Italy, Japan, and South Korea), we instead computed the absolute error for each country. The absolute error used here (AE; t ha^{-1}) is defined as

$$\mathrm{AE}_i = |Y_{2019,i}^f - Y_{2019,i}^r|. \tag{6}$$

Finally, the absolute percentage error was computed for all crop-country combinations considered here. The yield levels differed by crop and country. The absolute percentage error enables the comparison of forecast errors across different crops and countries. The absolute percentage error used here (APE, % to the 2019 reported yield) is defined as

$$\mathrm{APE}_i = \left|\frac{Y_{2019,i}^f - Y_{2019,i}^r}{Y_{2019,i}^r}\right| \times 100. \tag{7}$$

3. Results

a. Maize in Europe

Yield forecast skill tends to increase as crops approach the harvest. The 2019 JRC yield forecasts for the EU countries became available in April 2019 and were updated monthly until October 2019 (Fig. 1). The correlation value computed between the reported and predicted yields for the season across the 10 maize-producing countries in Europe was 0.939 in April and increased to 0.961 in July and to 0.984 in October ($p < 0.001$ for the three months), with some monthly fluctuations. This improvement in the skill score was also observed for the RMSEs. The RMSE value started at 0.68 t ha^{-1} in April and decreased to 0.51 t ha^{-1} in July and to 0.49 t ha^{-1} in October.

Three differences emerged between the JRC and NARO-APCC forecasts. First, the first month and time period for which maize forecasts were available was different between the two forecasts. The NARO-APCC forecasts became available for Bulgaria, Romania, and Spain in March (Fig. 1), while the first JRC forecasts were published in April. The final NARO-APCC forecasts occurred at midseason (July) because the maize-growing season in most countries in Europe completes within three months after July, before October (Fig. S1). The yield models used in the NARO-APCC forecasts associate 3-month average climate anomalies with yield anomalies, and therefore, the NARO-APCC yield anomaly forecast is not provided when harvesting is expected to occur within three months from the month in which the forecasts are made. Second, the skill of the NARO-APCC forecasts for the season was good, as indicated by the correlation values of 0.898 in April and 0.899 in July as well as the RMSE values of 0.95 t ha^{-1} in April and 1.04 t ha^{-1} in July (Fig. 1); however, these forecast errors were almost always larger than those of the JRC forecasts (note that the skill for March was uncertain compared to

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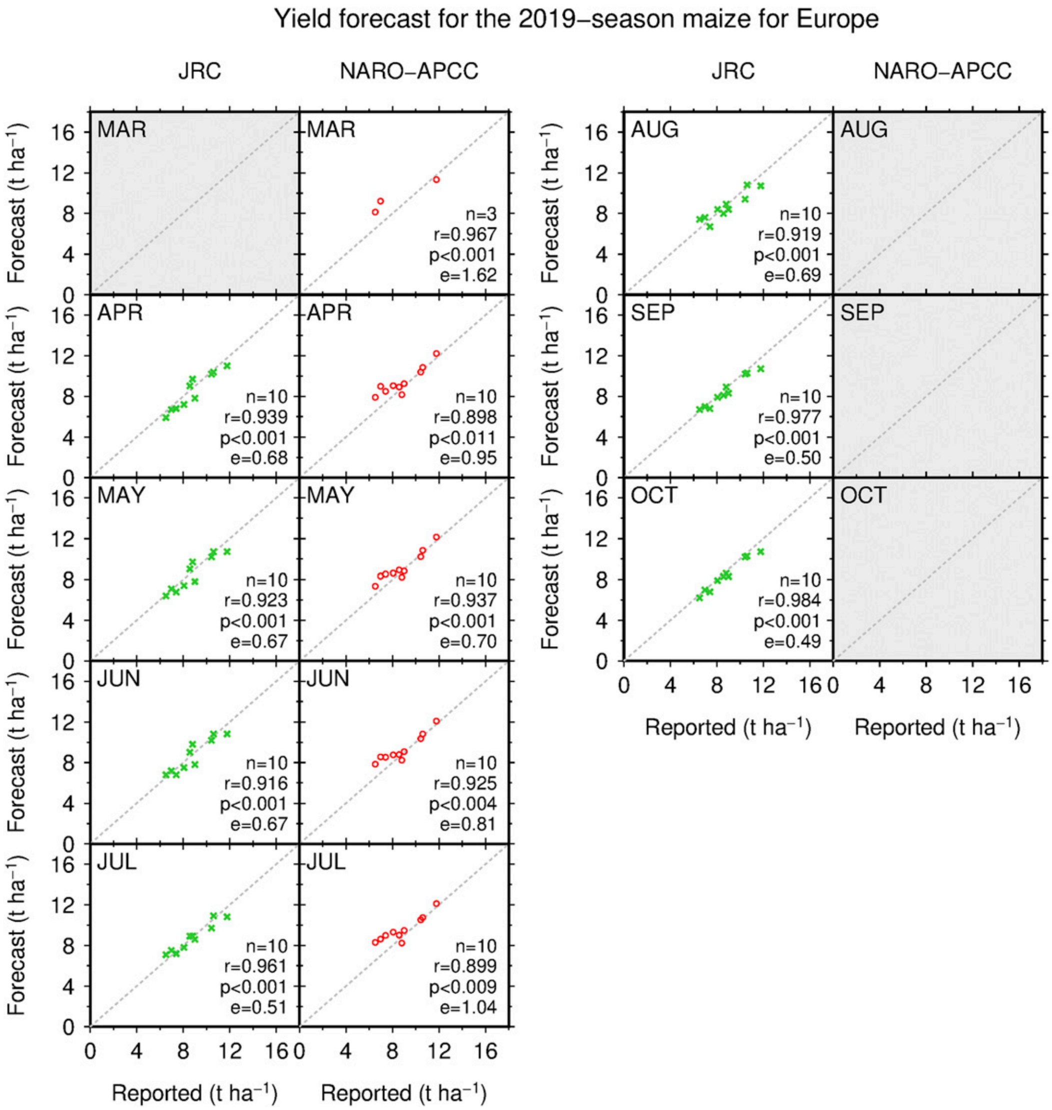

FIG. 1. Monthly scatterplots of the agreement between reported and forecasted 2019 maize yields for Europe. A total of 10 maize-producing countries in Europe forecasted by both the JRC and NARO-APCC systems are compared. The list of states is available in Table S2 in the supplemental material. The agreement is shown with n, sample size; r, correlation coefficient; p, p value; and e, root-mean-squared error in tons per hectare.

that in the other months because of the small sample size). Finally, skill score values tended to improve in the JRC forecasts as crop growth progressed, but this tendency was not observed in the NARO-APCC forecasts.

b. Wheat in Europe

The first JRC forecasts for 2019 were published in March 2019 and were updated every month until October 2019 (Fig. 2). The correlation values for the JRC forecasts improved slightly with the progress of crop growth from 0.975 to 0.982 in the earlier months (March–June) to 0.985–0.986 in the later months (July–October). The RMSE values decreased from 0.47–0.56 t ha^{-1} for the earlier months to 0.46–0.48 t ha^{-1} for the later months. Most of the final JRC forecasts were more accurate than the first JRC forecasts.

The NARO-APCC forecasts began in January 2019 for seven wheat-producing countries in Europe. The number of countries where the NARO-APCC forecast was available increased to 12 countries from February to April and decreased again to nine in May 2019 (Fig. 2) because of the different harvesting months among the countries (Fig. S1). Unlike the maize forecasts described earlier, the skill of the NARO-APCC wheat forecasts improved as the crop developed. The correlation values in the later months (April–May; 0.917–0.981) were higher than those in the earlier months

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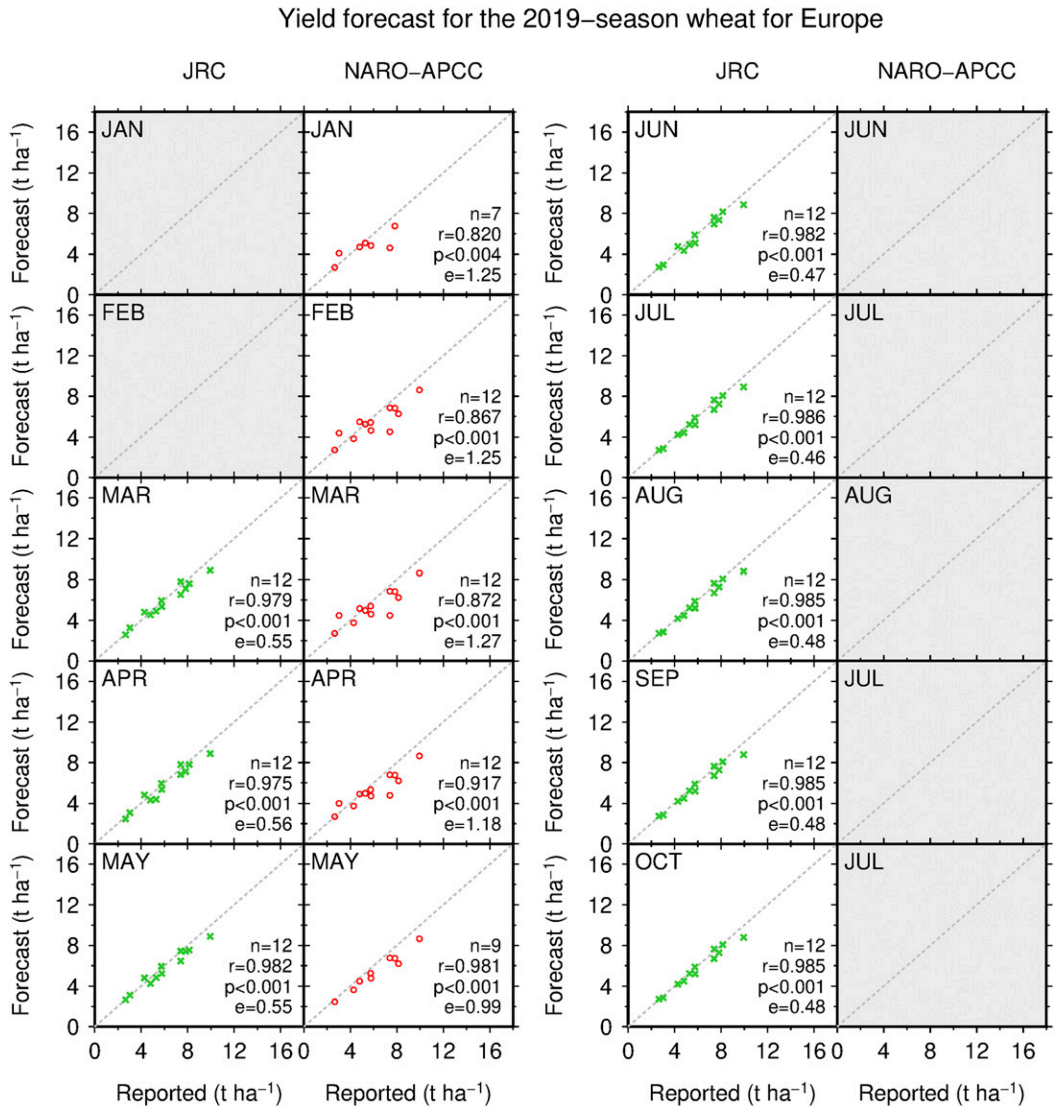

FIG. 2. As in Fig. 1, but for wheat yields for Europe.

(January–March; 0.820–0.872), with lower RMSE values in the later months (0.99–1.18 t ha^{-1}) than in the earlier months (1.25–1.27 t ha^{-1}).

c. Maize in the United States

While highly accurate, the USDA maize forecasts were not available early in the season and became available midseason (August), mainly due to their heavy reliance on producer surveys. The first 2019 USDA forecasts for 32 maize-producing states started in August 2019 and finalized in November 2019 (Fig. 3). Even for the first forecasts in August, the correlation value was extremely high, at 0.976, with an RMSE value of 0.40 t ha^{-1}. The skill improved even further with the progress of crop growth. The USDA forecasts at the end of the season that were released in November were identical to the reported yields (note that the final measurements were made in December (FAO 2016) but not in November).

The first NARO-APCC forecasts for the 10 maize-producing states became available in March (Fig. 3). The number of states for which the NARO-APCC forecast was available increased to 18 in April and to 32 after May and then decreased after July. The final NARO-APCC forecasts were made in August. The NARO-APCC forecasts appeared skillful at the state scale, with monthly variations. The correlation value for the NARO-APCC forecasts increased from 0.726 in March to 0.879 in August. The RMSE value decreased from 2.29 t ha^{-1} in March to 1.12 t ha^{-1} in August. These values are fairly good in absolute terms but were always worse than those of the USDA forecasts.

d. Soybean and rice in the United States

For the United States, the results for soybean and rice are essentially the same as those for maize. The USDA soybean and rice forecasts began in August and were finalized in November, whereas the NARO-APCC forecasts covered

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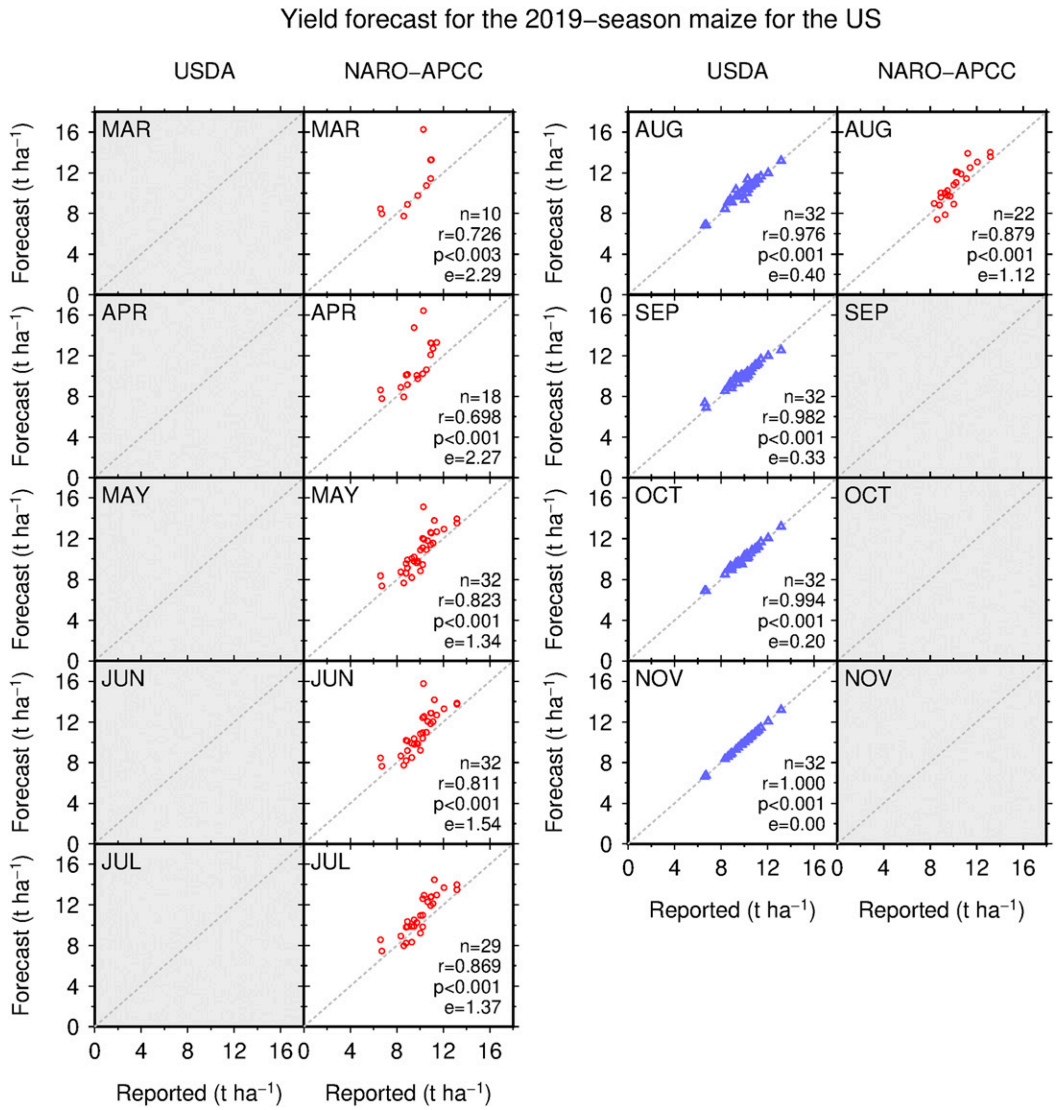

FIG. 3. As in Fig. 1, but for maize yields for the United States. All 32 maize-producing states in the United States forecasted by both the USDA and NARO-APCC systems are compared. The list of states is available in Table S3 in the supplemental material.

April–August for soybean (Fig. S2) and March–July for rice (Fig. S3). For the USDA soybean forecasts, the correlation and RMSE values in August were 0.930 and 0.24 t ha^{-1}, respectively. The forecast errors in the NARO-APCC soybean forecasts were larger than those in the USDA forecasts regardless of the month (Fig. S2). This tendency was common for rice (Fig. S3).

e. Wheat in the United States and rice in Italy, Japan, and South Korea

The forecast errors in the NARO-APCC wheat forecasts at the national level released from January to June (AE = 0.01–0.19 t ha^{-1} and APE = 0.3%–5.5%) were close to those of the USDA forecasts for total wheat released in July (0.11 t ha^{-1} and 3.3%); however, the USDA forecast for August (0.01 t ha^{-1} and 0.2%) was more accurate than any of the earlier forecasts (Figs. 4a and 5). Importantly, both the NARO-APCC and USDA forecasts showed lower forecast errors than the simple forecast, indicating that these forecasts are value-added to the simple forecast.

For 2019 rice in Italy, the forecast errors of the NARO-APCC forecasts released from May to August (AE = 0.40–0.42 t ha^{-1} and APE = 6.1%–6.4%) and of the JRC forecast for June (0.43 t ha^{-1} and 6.6%) were 2 times larger than those of the simple forecast (Figs. 4b and 5). Only the JRC September forecast appeared to be superior to the simple forecast. The NARO-APCC forecasts for rice in Japan released for May–August were only marginally better than or equivalent to the simple forecast (Figs. 4c and 5). On the other hand, the NARO-APCC forecasts for rice in South Korea released from April to

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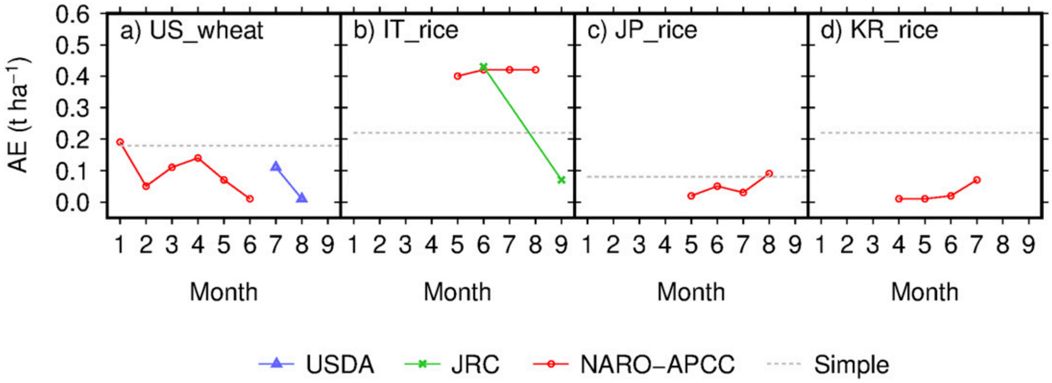

FIG. 4. The absolute error (AE) of the 2019 yield forecasts for (a) wheat in the United States and rice in (b) Italy, (c) Japan, and (d) South Korea computed for the JRC, USDA, and NARO-APCC forecasts. The simple forecasts are used as the reference forecasts.

July appeared to be more skillful than the simple forecast regardless of the month (Figs. 4d and 5).

f. Comparison with the simple forecast

The NARO-APCC forecasts appeared skillful for 42% of the 12 maize-producing countries, 46% of the 13 wheat-producing countries, and 50% of the 4 rice-producing countries, relative to the simple forecasts. The NARO-APCC forecasts for the soybean-producing countries examined here were not skillful. The number of skillful countries for the NARO-APCC forecasts was one-fifth to one-half of the JRC and USDA forecasts.

For maize, the NARO-APCC forecasts were skillful for five countries (DE, ES, FR, HR, and RS; see Table S2 for the abbreviations), while the end-of-season JRC forecasts showed meaningful skill for nine countries (AT, BG, DE, GR, HR, FR, PL, RO, and SK) (Fig. 5), out of the 11 maize-producing countries in Europe. Note that out of the 12 maize-producing countries in Europe (Table S2) the NARO-APCC forecast was not available for Poland but available for Serbia, whereas the JRC forecast was not available for Serbia but available for Poland. For wheat, the NARO-APCC forecasts in five (BE, FR, GR, HU, and RO) were better than the simple forecasts, whereas the JRC wheat forecasts outperformed the simple forecasts in 11 countries (AT, BE, DE, DK, ES, FR, GR, HU, LT, RO, and SE), out of the 12 wheat-producing countries in Europe. The NARO-APCC forecasts for rice in Japan and South Korea were skillful. For the United States, the USDA forecasts at the national level were skillful for all considered crops except rice, whereas the NARO-APCC forecasts did a better job than the simple forecast only for wheat.

At the state level, the final USDA forecasts were better than the simple forecasts for all 32 maize-producing states (Table S3), while the NARO-APCC forecasts were skillful for 18 states (56%) (Fig. 5). The corresponding values for the remaining crops were as follows: soybean, 97% of the 29 soybean-producing states for the USDA forecasts versus 24% for the NARO-APCC forecasts; and rice, 100% of the six rice-producing states for the USDA forecasts versus 17% for the NARO-APCC forecasts. Last, the NARO-APCC forecasts showed meaningful skill for 65% of the 37 wheat-producing states (Fig. 5), while the USDA total wheat forecasts at the state level were not available and were not assessed here.

4. Discussion

a. Relative advantages and disadvantages

The NARO-APCC forecasts are released 1–5 months earlier than the JRC and USDA forecasts. The NARO-APCC forecasts become available in March for maize and in January for wheat for some countries in Europe, whereas the JRC forecasts are always published for all EU countries in March for soft and durum wheat, starting in April for maize and soybean, and in June for rice. This feature of the NARO-APCC forecasts is noticeable when compared to the USDA forecasts that begin in August for maize, soybean, and rice and in July for total wheat; the NARO-APCC forecasts begin in March or April for the summer crops and in January for wheat. The difference in the timing of forecast availability is a relative advantage of the NARO-APCC forecasts and makes them complementary with respect to the existing regional crop forecasting systems. There are two reasons for this advantage. The NARO-APCC forecasts focus on the yield anomaly, which is associated mainly with the season climate conditions; to predict this anomaly, climate forecasts are used as the sole input. Note, however, that this advantage comes at the cost of relatively larger forecast errors in the NARO-APCC forecasts than in the JRC and USDA forecasts. The first JRC forecasts are mostly based on historical yield trends (van der Velde and Nisini 2019). Therefore, the combined use of the JRC yield forecasts and the NARO-APCC yield anomaly forecasts in the earlier stages of a season is potentially beneficial for users of the JRC forecasts. In this way, the information from seasonal climate forecasts can also be accounted for, as climatic condition of a coming season is currently not explicitly accounted for in the JRC trend-based forecasts.

The assumption that forecast errors decrease with the progress of crop growth is reasonable for at least two reasons. The information available on crop status for the ongoing season increases with time and is progressively incorporated into

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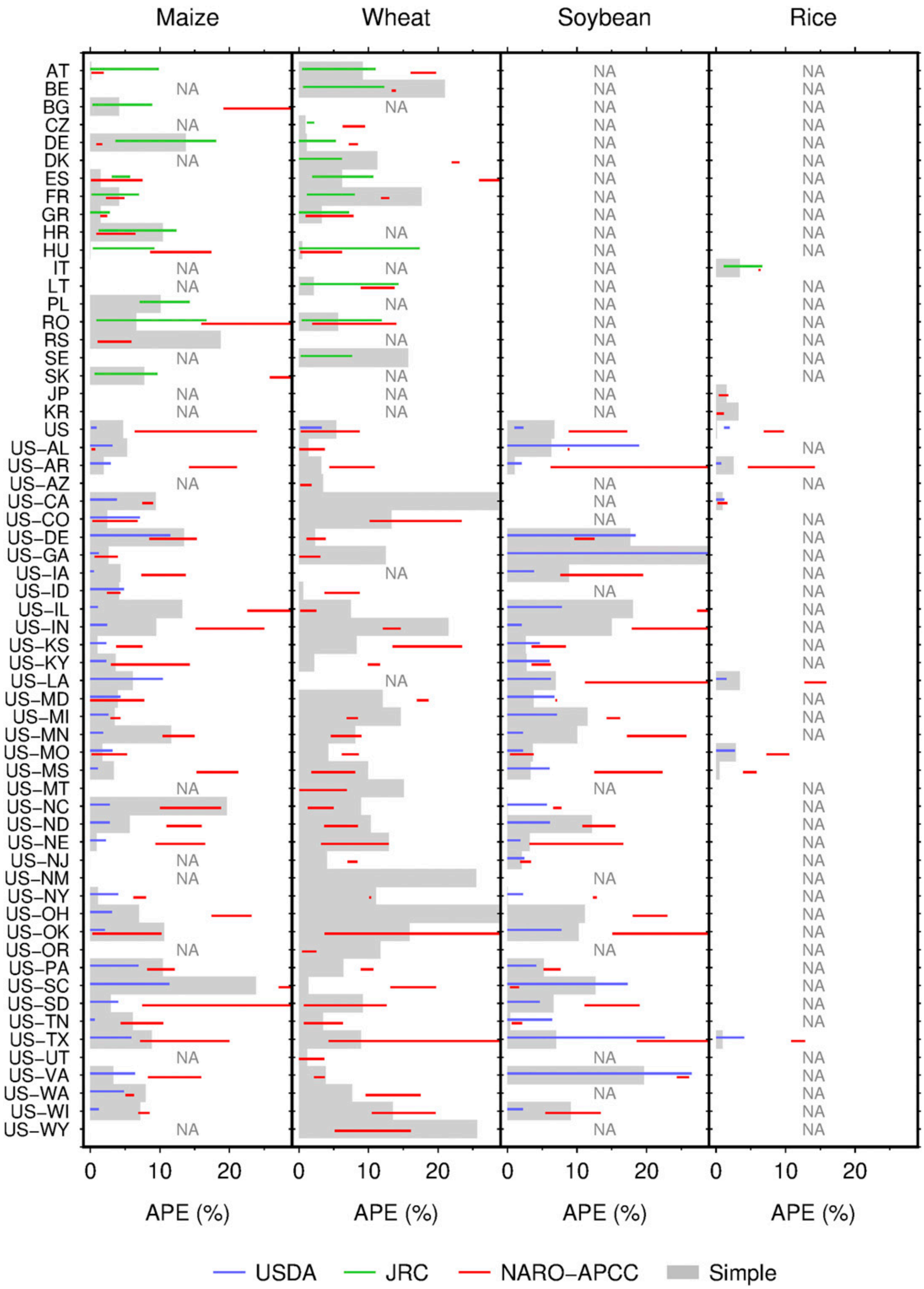

FIG. 5. The absolute percentage errors (APE) of the 2019 yield forecasts for maize, wheat, soybean, and rice in the 20 countries and 39 states in the United States computed for the JRC, USDA, NARO-APCC, and simple forecasts. NA indicates that the reported yield was not available. See Tables S2 and S3 in the supplemental material for the country and state codes. The colored horizontal lines indicate the lowest and highest APE values of the individual yield forecasts. If the left edge of the colored lines is located to the left of the gray bar, it indicates that the individual yield forecasts were skillful.

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yield forecasts, as seen in the methods used for the JRC and USDA forecasts. Uncertainties in yield impacts due to weather conditions for the remaining portion of the season decrease as harvesting approaches (Hansen et al. 2006). Therefore, the increases in forecast skill found for the JRC and USDA forecasts are considered reasonable. This tendency is also consistent with that observed in earlier studies. The decreases in forecast errors for grain maize, soft wheat, and durum wheat in EU countries from the beginning-of-season to the end-of-season forecasts were reported for the JRC forecasts in van der Velde and Nisini (2019). Holland (2011) reported that the RMSE values computed between the USDA forecasts and the reported yields of maize, soybean and winter wheat for the United States decrease from approximately 6% in the first forecast of a season to less than 2% in the final forecast. Similar tendencies as those reported in Holland (2011) are also found in Egelkraut et al. (2003) for the USDA maize and soybean forecasts.

However, this tendency is unclear in the NARO-APCC forecasts, with a few exceptions (e.g., wheat in Europe and maize and wheat in the United States). In the NARO-APCC forecasting method, the information on crop status is not considered. Therefore, the NARO-APCC forecasts, in their current form, do not benefit from updated crop status information as crop growth progresses, although temperature and precipitation forecast errors in general decrease as the lead time of climate forecasts shortens as the harvest approaches. In addition, the climate forecast skills at particular locations vary by season. In the Northern Hemisphere, the climate forecast skill is higher in the winter than in the summer season (Doblas-Reyes et al. 2013; Min et al. 2014, 2017). This helps explain why the yield forecast skills of the NARO-APCC forecasts do not improve with crop growth progress in many cases. It is also important to determine through future research whether climate conditions in the season were favorable enough regardless of climate forecast skill. This feature of the NARO-APCC forecasts seems be a disadvantage, but this could be an advantage if a meaningful yield forecast skill can be achieved in the earlier stages of a season.

Finally, in many locations, climate forecasts are particularly skillful during periods with strong sea surface temperature forcing events [e.g., El Niño–Southern Oscillation (ENSO)]. A warmer phase of ENSO, that is, an El Niño event, lasted from the end of 2018 to the earlier half of 2019, based on the oceanic Niño index (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php). Consequently, the yield forecast skills for the 2019 season presented here may be better than those for neutral years (neither El Niño years nor La Niña years). Assessments need to be continued for multiple years to evaluate yield forecast skill more precisely. Since the yield forecast skills shown here are based on APCC MME, using seasonal climate forecasts from other weather centers as the input to the statistical yield models would result in different skill levels, as recently tested (Iizumi et al. 2021).

b. *Potential ways to move forward*

We assessed the skill of the NARO-APCC 2019 yield forecasts. Benchmarks were established against reported yields and against yield forecasts for the world's major crop producers published by two leading organizations, the JRC for the EU and the USDA for the United States. A further evaluation through comparison with other organizations' forecasts and for other regions in the world will be a worthwhile avenue for future research. Indeed, many more regional forecasts besides those considered here are available, for example, forecasts for some major producers such as Australia, Canada, China, India, and South Africa. In addition, assessing yield forecast skill in developing countries is important to enable early interventions and policy making (Mann et al. 2019). In developing countries, crop production is predominantly performed by subsistence farmers and is therefore more susceptible to climate conditions during the season than industrialized farming. The next round of evaluation may include countries located in the Southern Hemisphere as well as multiyear samples. Furthermore, it will be worthwhile assessing the yield forecast skills for winter and spring wheat separately as climate forecast skills are different season by season.

At the global scale, it is increasingly recognized that synchronized yield variability across multiple countries is associated with major modes of oceanic and atmospheric variability (Anderson et al. 2019; Mehrabi and Ramankutty 2019; Najafi et al. 2020). Understanding such synchrony in large-scale climatic drivers and the world's crop production and, if possible, forecasting this dependency would further improve the robustness of the global food supply chain, with benefits for import-dependent countries. There are some attempts to incorporate indices that represent large-scale oceanic and atmospheric variability into regional yield forecasting, e.g., in Europe (Ceglar et al. 2017, 2018; Nobre et al. 2019). However, regional forecasts cannot fully represent the impacts of synchronized yield variability on global food markets. Therefore, global yield forecasting is potentially more advantageous than regional systems in representing synchronous production impacts.

Recent advancements in machine learning techniques (e.g., Jeong et al. 2016; Hoffman et al. 2018; Mann et al. 2019; Vogel et al. 2019) seem somewhat promising for improving the statistical yield models currently used in the NARO-APCC system. Recent increases in the availability of crop-related data at the regional to global level would help to improve global yield forecasting. Such global datasets include gridded historical yield time series data (Iizumi and Sakai 2020), rainfed and irrigated yields (Siebert and Doll 2010; Sloat et al. 2020), potential sowing and harvesting windows (Iizumi et al. 2019), high-resolution crop phenology (Luo et al. 2020) and crop-specific harvested areas in 2010 (Yu et al. 2020). Annual crop type masks derived from satellite images (Inglada et al. 2015) and incorporating satellite-derived vegetation indices into statistical yield models (Peng et al. 2018) are expected to be useful. The improved understanding of climate-yield relationships developed in recent years and the yield impacts of climate extremes in particular (e.g., Jeong et al. 2016; Schauberger et al. 2017a,b; Ben-Ari et al. 2018; Lecerf et al. 2019; Li et al. 2019; Vogel et al. 2019) should enable us to select appropriate predictors for seasonal yield forecasting in a changing climate.

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However, difficulties still remain. For instance, currently, annual yield time series are not separately available for rainfed and irrigated crops. Only average rainfed and irrigated yields for the period 1998–2002 are available at global level (Siebert and Doll 2010). This prevents us from modeling rainfed and irrigated yields separately in a more explicit way, although the irrigation intensity (the ratio of irrigated area to harvested area) is in part considered within the statistical yield models used in the NARO-APCC system by estimating regression coefficients for each grid cell.

5. Conclusions

This study evaluates the 2019 yield forecasts derived from the NARO-APCC Crop Forecasting Service, which is currently in a test mode. The comparison of multiple operational yield forecasts (the JRC, USDA, NARO-APCC, and simple forecasts) shows that the NARO-APCC forecasts can provide meaningful forecasts (relative to the simple forecasts) one to five months earlier than the existing regional systems. The development and operationalization of global crop forecasting services, including the NARO-APCC forecasts, are of growing importance. These services can increase the capacity of societies to respond to production shocks in the face of a rapidly globalizing food supply chain and climate change, which will ultimately contribute to global food security. Global crop forecasting services are also expected to complement existing regional forecasting services and could be a valuable input to initiatives for monitoring global agriculture and commodity markets such as GEOGLAM and AMIS.

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Data availability statement. The APCC MME temperature and precipitation forecasts used in this study are available at http://adss.apcc21.org/. The predicted yields are available from the corresponding author upon request.

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