Global Risk Assessment of Climate-Induced Food Production Shocks: from Seasonal Scale to the End of This Century

Toshichika Iizumi
National Institute for Agro-Environmental Sciences (NIAES)
3-1-3 Kannondai, Tsukuba, Japan
iizumit@affrc.go.jp

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1. Introduction

The five-year long research project for Global Risk Assessment toward Stable Production of Food (GRASP) at NIAES launched April, 2011 has entered the final phase. To date, a number of remarkable outcomes have achieved: seven papers were cited in five chapters of the Working Groups 1 and 2 contributions to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC); a paper was used as the input for the Food and Agriculture Organization of the United Nations (FAO) working paper (Rojas et al., 2015) and U.S. Department of Agriculture 2015 Agricultural Outlook Forum; the Japan's first seasonal crop prediction information provided in this project in July, 2014 was used in the monthly report on international food demand and supply of the Ministry of Agriculture, Forestry and Fisheries (MAFF, 2014); the latest research information on the impacts of climate change and seasonal climate variability on crop production was provided to expert meetings at MAFF, APEC (Asia-Pacific Economic Cooperation) Food Security Workshop, G20 AMIS (Agricultural Market Information System), APEC Climate Center etc.; and a lot of papers published in high-impact journals, resulting in over 20 media exposures.

As in the title "Next Challenges of Agro-Environmental Research in Monsoon Asia", the MARCO Symposium 2015 aims at exchanging the latest results of studies on agriculture and environment and discussing the direction of future research and collaboration with strong focus on monsoonal Asia. This is an excellent opportunity to share the findings and experiences of GRASP project and discuss with distinguished experts. To that end, this article summarized the major outcomes of the project and outlined potential ways forward as the inputs for discussion.

2. Highlights of Key Findings

2.1 Assessing the risk of Climate Change on Global Crop Production

The global impact assessment of climate change on food production has been conducted applying a set of the latest scenarios on emission, climate and socioeconomy to a global gridded crop model for major crops (maize, rice, wheat and soybean) developed at NIAES (named PRYSBI-2, Sakurai et al., 2014) (S-10 Strategic Research Project, 2014). In this assessment, the scenarios consisted of the following data sources: four different Representative Concentration Pathways (RCPs, the radiative forcing of 2.6, 4.5, 6.0 and 8.5 W m^{-2}, Moss et al., 2010); five different global climate models (GCMs) outputs derived from the Coupled Model Intercomparison Project phase 5 (CMIP5, Taylor et al., 2012), including GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM and NorESM1-M; and three different Shared Socioeconomic Pathways (SSPs) on population and gross domestic product (GDP), including 1, "Sustainable World", 2, "Current Trends Continue" and 3, "Fragmented World" (O'Neill et al., 2012).

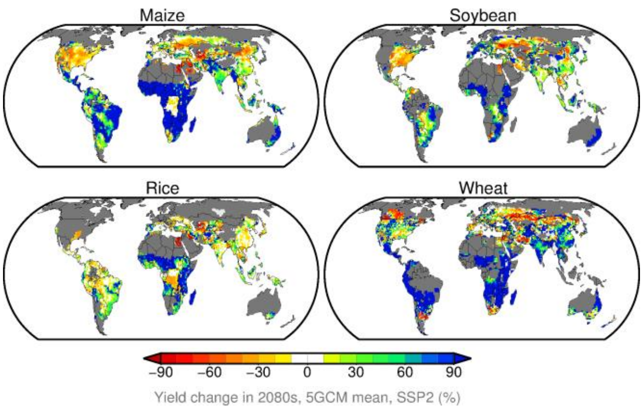

Fig. 1. The projected yield change in 2080s (2070-2099), relative to 2003-2005, for four crops based on RCP8.5/5GCMs/SSP2 scenarios. The dark grey area indicates the crops were not currently harvested.

When RCP8.5/5GCMs/SSP2 scenarios were used, the results suggested that maize yields in the United States (U.S.), East Asia and East Europe would decrease, whereas yields in South America, Africa, South Asia, South East Asia and Australia would increase (Fig. 1). For rice, yields in the U.S. and Central Asia were projected to decrease, but yields in many parts of Africa would increase. The projected decreases in wheat yields in North America, East Europe, Central Asia, and southern part of South America were found. In contrast, wheat yields in the norther part of South America and Africa would increase. For soybean, yields in the U.S. and East Europe would decrease and yield increases in Africa and Australia would be anticipated. However, it revealed that the uncertainty of yield impacts in some location-crop combinations associated with different GCMs was large, for instance, as shown for rice in South Americas, southern part of China and South Asia (Fig. 2). While these results were commonly based on RCP8.5/SSP2 scenario, the uncertainty of the yield impacts associated with different SSPs was smaller than the uncertainty due to different GCMs. However, for some crops, such as wheat, the minor differences in yield impacts across SSPs appeared, suggesting that the use of different socioeconomic scenarios is a source of uncertainty as well as emission scenarios and GCMs (Fig. 3).

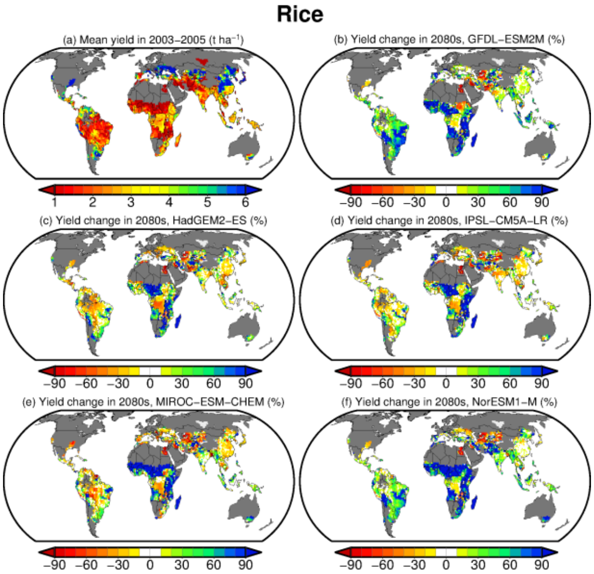

Fig. 2. The Uncertainty of rice yield change in 2080s (2070-2099), relative to 2003-2005, associated with five different GCMs. RCP8.5/SSP2 scenario were commonly used. The simulated mean yield in 2003-2005 is presented as the reference. The dark grey area indicates the crops were not currently harvested.

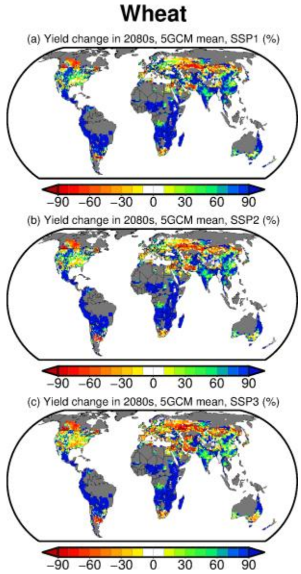

Fig. 3. The uncertainty of wheat yield change in 2080s (2070-2099), relative to 2003-2005, associated with three different SSPs. RCP8.5/5GCMs scenarios were commonly used. The dark grey area indicates the crops were not currently harvested.

The projected change in harvested-area-weighted global mean yields suggested that the yield growth rate of the crops would gradually decrease and reach the plateau by around 2050–2060s on a global basis (Fig. 4). In 4RCPs/GFDL-ESM2M/3SSPs scenarios, the global mean yields would even turn to decrease. The decreasing trend was consistent across the socioeconomic scenarios with minor differences in a quantitative manner. This result suggests that the technological improvement assumed here that was derived based on the empirical relationship between the technological coefficient of PRYSBI-2 model and country GDP in the past decades would be insufficient to double yields of the crops. It leads to the implications that a substantial cropland expansion is avoidable in coming decades and targeted adaptation in parallel with strategic research and development investment for high yielding technology is imperative to maintain yield growth.

2.2 Assessing the Predictability of the Impacts of Seasonal Climate Variability on Yields

The world first global assessment of the reliability of crop yield hindcasts (Iizumi et al., 2013) demonstrates that, for rice and wheat, moderate-to-marked yield losses (5% more yield decrease in year *t* relative to three-year running mean normal yield for the interval from *t*-3 to *t*-1) are reliably predictable at three month before the harvest using a combination of simple statistical yield models and ensemble seasonal temperature and soil moisture forecasts of JAMSTEC (the Japan Agency for Marine-Earth Science and Technology, Luo et al., 2005, 2008). The maize and soybean yield hindcasts appeared useful for some regions of the world (e.g., Indonesia), but not satisfactory reliable at the global scale due to higher yield sensitivity of these crops to soil moisture in key producing regions (Fig. 5) and lower predictability of soil moisture than temperature.

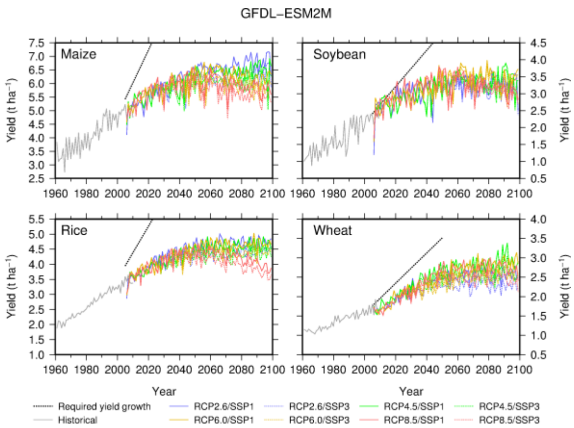

Fig. 4. The change in harvested-area-weighted global mean yields of four crops when 4RCPs/GFDL-ESM2M/3 SSPs scenarios was used. The historical simulation in 1961-2005 is presented as the baseline. Dashed line indicates the yield growth of Ray et al. (2013) which necessary to double yield in 2050 relative to that in 2005.

Iizumi et al. (2015) classified the reliability of yield prediction with lead time of three months into four categories (Fig. 6) and mapped (Fig. 7), leading to the conclusion that global maize and soybean prediction would gain a large benefit from improvements of soil moisture forecasts in 30–50°N during July–October and in 30–40°S during February–April.

Improving climate predictability is definitely important for more reliable crop prediction, but it takes a considerable amount of time. Given the increased volatility of commodity markets and the increased dependence of consumers in many countries to food imports, we linked mean yield anomalies in 1982-2006 with each phase of the El Nino Southern Oscillation (ENSO). For instance, Fig. 8 shows the mean impacts of the warmer phase of ENSO (i.e., El Nino) on global yields of major crops (Iizumi et al., 2014a). A use of ENSO forecasts is advantageous when linking ENSO forecasts and the impacts of ENSO on yields presented here because ENSO forecasts are in general very skillful (Luo et al., 2008) and have been provided at lead times even much longer than those of seasonal temperature and precipitation forecasts.

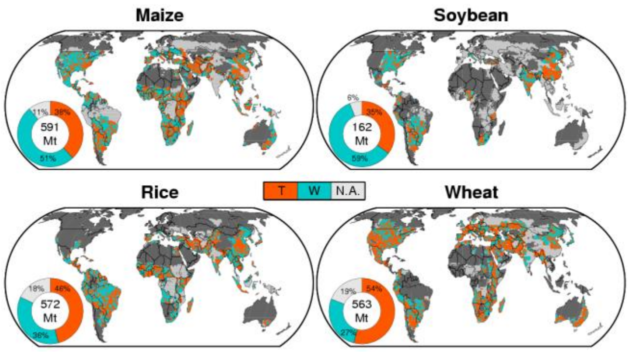

Fig. 5. The dominant climatic factors affecting the year-to-year variations in the yields of four crops. The pie diagrams indicate the percentages of production that are sensitive to temperature (orange) and soil moisture (blue) as well as those for which no hindcasts were available (grey) in 2000. The dark grey area indicates the crops were not harvested.

By 2050, the global demand for major crops is expected to double from that in 2005 (Ray et al., 2013). To meet this growing demand, the mean growth rate of global crop production in the coming four decades must reach 2.4% per year (the dashed line, Fig. 4). It is expected that a major portion of this growth will be achieved by an increase in crop yields in areas that have low yields today, which are caused in part by technology that is less able to reduce the impacts of climate variability compared with technology in other areas. Consequently, both minimizing the negative impacts of ENSO and maximizing the positive impacts of ENSO on global yields are increasingly important not only to ensure short-term food availability but also to maintain yield growth rate as high as possible (Iizumi et al., 2014a).

3. Key Tools, Data Sets and Techniques Developed in GRASP Project

3.1 Large-Area Crop Models

Process-based crop models are essential tools to analyze the climate-crop relationships at various time scales from daily weather fluctuation to seasonal climate variability to climate change. While over 70 different crop models have already been operated by 2010 (White et al., 2011), most models focus on field scale. Only a few large-area models which operate at global scale (or global gridded crop models) are feasible. Growth processes incorporated into field-scale models are in general more detailed than those of large-area models, hence require intensive inputs, including management data. Such information is hardly available for a large spatial domain. Large-area models therefore have less input requirements. And many processes in large-area models sensitive to local management are parameterized while key processes at predefined target resolution in space and time remain sufficiently detailed.

In GRASP project, a suite of large-area models have developed and being used. The Process-based Regional-scale Yield Simulator with Bayesian Inference for paddy rice (PRYSBI-1, Iizumi et al., 2009) provides the basis of model

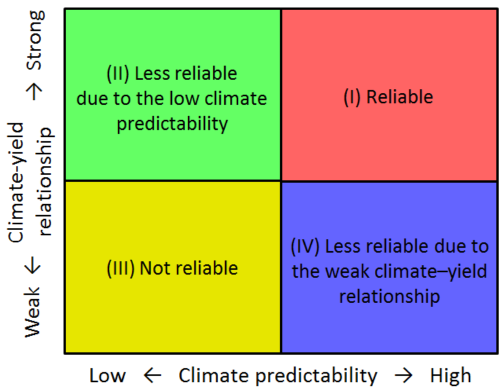

Fig. 6. Four categories of the reliability of crop yield prediction.

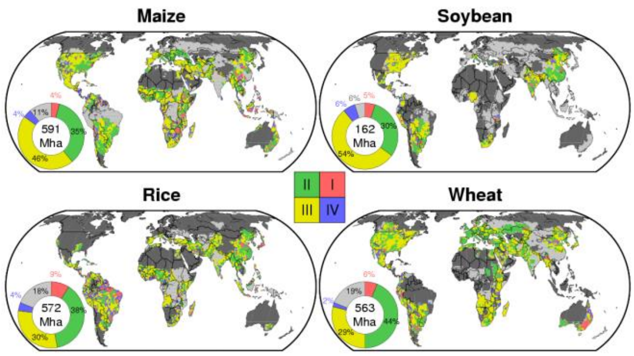

Fig. 7. The categorized reliability of within-season crop prediction for four crops. The color correspond to each category is presented in Fig. 6. Light gray areas indicate that no crop prediction was available. Non-cropped areas are shown in dark gray. The pie diagrams indicate the percentages of global harvested area in the colored areas, normalized to the global harvested area in 2000.

development in the project that a large-area model describes relationships between crop and environment, both are area-averaged, through the adjustment of model parameter values with explicit treatment of uncertainty using a Bayesian calibration technique. Then a large-area model for upland crops was developed to analyze the impacts of historical changes in climate and planting date on maize yield growth rate in the U.S. (PRYSBI-1.1., Iizumi et al., 2014b). Another model has more detailed processes on photosynthesis, respiration and assimilate partitioning compared to earlier models and used to detect the fertilizer effects on soybean yields in the U.S., Brazil and China associated with increased atmospheric carbon dioxide concentration in the last decades (PRYSBI-2, Sakurai et al., 2014). Recently, PRYSBI-2 model has extended to cover major crops (maize, rice, wheat and soybean) over the globe and contributed to the Agricultural Model Intercomparison and Improvement Project (AgMIP, Elliott et al., 2015). Furthermore, PRYSBI-2 model was embedded into a global hydrological model and has being used to assess the irrigation-based adaptation potential to increase watershed soybean production in Northeast China under changing climate, water resources and land use (Okada et al., in review).

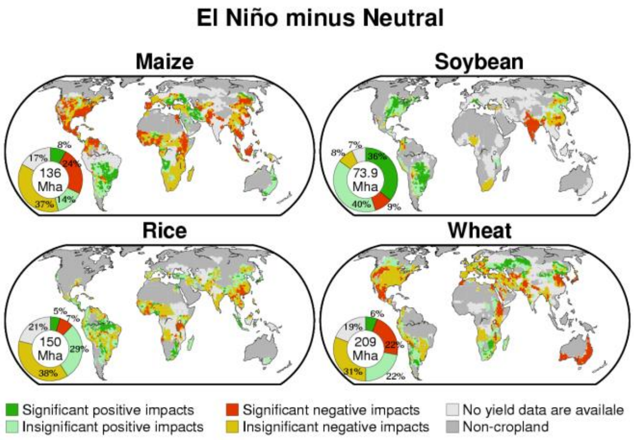

Fig. 8. The mean impacts of El Nino on crop yield anomalies in 1982-2006 for four crops. The five-year running mean method was used to calculate normal yield. The significance level of the difference in averaged yield anomaly between El Nino years and neutral years was set to be 10%. The pie diagrams indicate the percentages of harvested area in the aforementioned areas. All data in the pie diagrams are normalized to the global harvested area in 2000.

3.2 Historical Data Sets for Global Climate-Crop Analysis

Almost no historical information was available for global climate-crop analysis at the beginning of GRASP project. The Global Data set of Historical Yields of major crops (GDHY, Iizumi et al., 2014c) was developed following the world first data set of Ray et al. (2012). GDHY data set is a satellite-statistics hybrid product that covers most of global cropland at the grid size of 1.125° and provides grid-cell yield estimates (and in part subnational yield statistics) of maize, rice, wheat and soybean for the period 1982–2006. Both yield data sets have significantly contributed to improve our understanding on yield impacts due to climate at subnational scale (e.g., Iizumi et al., 2013, 2014a, Ray et al., 2015) and provided the unique reference for large-area models. For instance, PRYSBI-2 model is calibrated by grid cell. GDHY data set as well as Ray et al. (2012) is used as the reference to evaluate historical simulation of global gridded crop models participated in AgMIP (Elliott et al., 2015).

Another exception is the world first meteorological forcing data set tailored for global crop modeling (GRASP forcing, Iizumi et al., 2014d). GRASP forcing data set offers 50-year (1961–2010) long daily time series of almost all climatic variables necessary to run crop models. A recent intercomparison (Iizumi et al., 2014d) suggested that the data set provides more reliable estimates of some climatic variables, vapor pressure and wind speed in particular which affect simulated potential and actual evapotranspiration rates and soil moisture, than other data sets.

3.3 Other Important Technologies

Other key technologies or data sets include the Bayesian calibration technique, satellite-derived soil moisture products and bias-correction method. The Bayesian calibration technique, i.e., the Markov-Chain Monte Carlo (MCMC) method, is powerful in optimizing a complex nonlinear model as well as useful in estimating the parametric uncertainty of a model under given data. Most models used in GRASP project benefit significantly from the technique. Increases in computing power conjunction with more rapid MCMC algorithms, for instance, the DiffeRential Evolution Adaptive Metropolis (DREAM) algorithm, developed in Vrugt et al. (2009) and applied to the large-area crop model calibration in Sakurai et al. (2014), open a new frontier in large-area modeling. Furthermore, a more sophisticated technique to deal with time change in parametric uncertainty of a model is feasible for statistical yield models (Sakurai et al., 2011), offering the opportunities to further improve large-area models.

Satellite remote sensing is a potential source of information for global climate-crop analysis. Among others, satellite-derived soil moisture products have increasingly become available. Such products provide the information on surface soil moisture over global cropland, for instance, at the grid size of 0.25° and daily time step. A comparison of four different soil moisture products derived from space agencies in the U.S., Europe and Japan with flux tower site observations in cropland worldwide revealed that although the reliability of satellite-derived soil moisture data vary by product, crop and length of time averaging, some products could be useful to evaluate seasonal variation patterns of soil moisture simulated by large-area crop models (Sakai et al., in review).

Lastly, the Cumulative Distribution Function-base Downscaling Method (CDFDM, Iizumi et al., 2011, 2012) is a flexible statistical downscaling and bias-correction method that is applicable to daily climate model output of almost all climatic variables used in crop models and plays a key role in the climate change/variability scenario generation.

4. Next Challenges

4.1 Climate Influences on Cropping Area, Intensity and Yield

Most studies of the climate influence on food production have examined the influence on crop yields. However, climate influences all components of crop production, includes cropping area (area planted or harvested) and cropping intensity (number of harvests within a year) as well as yield. Although yield increases have predominantly contributed to increased crop production over the recent decades, increased cropping area and increases in cropping intensity have played a substantial role in tropics, high latitudes and altitudes. Hence, we need to consider these important aspects of production to get a more complete understanding of the future climate change impacts and develop more targeted adaptation (Iizumi and Ramankutty, 2015).

4.2 Global Seasonal Crop Prediction to Adapt Climate Extremes and Change

Global seasonal crop prediction aims to inform national governments and commercial entities in food-importing countries about climate-induced variations in yields worldwide (Iizumi et al., 2013). Such technology has become increasingly important to aid better responses to possible food supply shocks induced by climate extremes. Also this technology is in-line with climate change adaptation because a first step towards adaptation is reducing vulnerability and exposure to present climate variability (IPCC, 2014). The amplitude of interannual variations in seasonal climate we have experienced is generally larger than that of projected warming by the middle of this century (Deser et al., 2012). Seasonal climate variability and associated food supply shocks provide the tremendous opportunities to test and improve our capacity to adapt climate change.

4.3 Estimating Global Adaptation Costs in Crop Production Systems

Both mitigation and adaptation are inseparably important to reduce the climate change risk inherent in food production systems. However, it is poorly understood how efficiently a limited public finance can be allocated to each of mitigation and adaptation. The information on adaptation costs by sector, at the global level in particular, is essential input for climate policy makers to change ongoing mitigation and adaptation efforts more integrated and cost-efficient. Costs and benefits of a mitigation activity can be quantified using a single measure, i.e., the amount of reduced greenhouse-gasses emissions. In contrast, measures to quantify adaptation effects could differ by sector and may vary even by economic player in a sector (yield, production, income, etc.). This fundamental gap poses a major challenge for assessing adaptation costs and compare with mitigation costs.

4.4 Data Gaps

Gaps in the data availability need to be fulfilled to approach these challenges. For instance, the information on where, when, which and how crop is grown is important to improve seasonal crop prediction as well as global risk assessment of climate change. Satellite remote sensing is a potential source of information. However, remote sensing has difficulty distinguishing individual crop types and misses entire cropping cycles in areas where extensive cloud cover during the monsoon limits satellite observations. Hence, it is of priority to develop a methodology to provide global, historical and crop-specific information on cropping area and intensity as well as crop calendar by combining multiple data sources, including satellite data, agricultural statistics and crop model outputs, into a single product.

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