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Understanding the Changes in Global Crop Yields Through Changes in Climate and Technology

Ehsan Najafi[1,2,3], Naresh Devineni[1,2,3], Reza M. Khanbilvardi[1,2,3], and Felix Kogan[4]

[1]Department of Civil Engineering, City University of New York, City College, NY, USA, [2]Center for Water Resources and Environmental Research (City Water Center), City University of New York, City College, NY, USA, [3]NOAA Center for Earth System Sciences and Remote Sensing Technologies, City University of New York, City College, NY, USA, [4]NOAA/NESDIS, Center for Satellite Applications and Research, College Park, MD, USA

Key Points:

- A new Bayesian multilevel model for understanding and predicting crop yield changes over time
- Capturing yield trends due to climate variability using large-scale and regional climate factors
- Exploring the impact of technology advancement on crop yield fluctuations using per capita gross domestic production

Correspondence to:
E. Najafi, enajafi@ccny.cuny.edu

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Abstract During the last few decades, the global agricultural production has risen and technology enhancement is still contributing to yield growth. However, population growth, water crisis, deforestation, and climate change threaten the global food security. An understanding of the variables that caused past changes in crop yields can help improve future crop prediction models. In this article, we present a comprehensive global analysis of the changes in the crop yields and how they relate to different large-scale and regional climate variables, climate change variables and technology in a unified framework. A new multilevel model for yield prediction at the country level is developed and demonstrated. The structural relationships between average yield and climate attributes as well as trends are estimated simultaneously. All countries are modeled in a single multilevel model with partial pooling to automatically group and reduce estimation uncertainties. El Niño-southern oscillation (ENSO), Palmer drought severity index (PDSI), geopotential height anomalies (GPH), historical carbon dioxide (CO_2) concentration and country-based time series of GDP per capita as an approximation of technology measurement are used as predictors to estimate annual agricultural crop yields for each country from 1961 to 2013. Results indicate that these variables can explain the variability in historical crop yields for most of the countries and the model performs well under out-of-sample verifications. While some countries were not generally affected by climatic factors, PDSI and GPH acted both positively and negatively in different regions for crop yields in many countries.

1. Introduction

Global food security is one of the most critical issues of the 21st century and is inseparable from human well-being. Technological advances, improved variety of seeds and fertilizers, and better farming practices are contributing to the enhancement of the crop production globally. At the same time, vagaries of climate, especially the frequency of extremes and changing seasons, and regional shortages of water and energy are inducing yield depressions and undermining the food security. Furthermore, climate extremes have been on the uptrend since the last century (Asadieh et al., 2016), and global climate change projections indicate that the frequency and severity of extremes may continue to increase, hence posing a challenge for the future (Parry, 2007). A burgeoning population, economic crises, political issues like sanctions, civil unrest, and social strife add to the uncertainties and make food security more complicated to address. For instance, the 1994 Rwandan famine brought about by the loss of 60% of the country's harvest was primarily due to the civil war (Sperling, 1997). Flooding and lack of trade triggered famine conditions in North Korea during the 1990s (Haggard & Noland, 2009). Recently, 17 million people in Yemen are under emergency food situation due to regional conflicts (Sharp, 2017). A clear understanding of the impacts of technology, climate variability, and climate change on global crop yields will be of tremendous value in a warmer world characterized by increased variability. We can develop optimal strategies that are resilient to such changes across different climates. Moreover, an understanding of which regions to target for higher productivity can show us the way to achieve global food-water-energy sustainability.

In this study, we present a unified Bayesian multilevel model for simultaneously understanding the secular trends and interannual variations in global crop yields due to climate change, technological advancements, and large-scale and regional climate variability factors. Global carbon dioxide (CO_2) levels are used as a proxy to understand the influence of climate change on country-level crop yields. Historical per capita gross domestic production (GDP) index is used to understand the impact of technology enhancements. Furthermore, El Niño-southern oscillation (ENSO), the Palmer drought severity index (PDSI), and the 500 hPa geopotential height anomalies (GPH) are used as surrogates to understand the interannual variations in the country-level crop yields due to large-scale and regional climate factors respectively. Applications for food, water, and energy management could be developed using this predictive model as part of the adaptation to a changing climate. A critical aspect of developing such statistical models is the ability to accurately represent the parameter uncertainties. The multilevel Bayesian method we used here provides the opportunity to explicitly quantify the parameter uncertainty using appropriate conditional and prior distributions, and allows for their reduction through pooling of information across countries (Gelman, 2006a).

In Section 2, we present a brief description of the prior studies in this area. In Section 3, we provide the details of the data and processing methods for country-level crop yields and the explanatory variables. We introduce the multilevel Bayesian model for global crop yield estimation in Section 4. The results from the model are discussed in Section 5. Finally, in Section 6, we present the summary and conclusions.

2. Background

Numerous prior researchers have attempted to relate weather, climate, and technological advancements with crop yields both at the regional scale and at the global scales. Seminal works at the regional level include Unganai and Kogan (1998), Cane et al. (1994), Kassie et al. (2010), Cantelaube et al. (2004), and Sakurai et al. (2014). Unganai and Kogan (1998) used remotely sensed data for drought monitoring and climate impact assessment in order to corn yield prediction in southern Africa. Cane et al. (1994) found that ENSO index can explain up to 60% of the variability in Maize yield for Zimbabwe, and with a lead time of up to a year, can provide accurate predictions of the yield. Cantelaube et al. (2004) found strong teleconnections between the first four principal components of the GPH and wheat yield anomalies in Europe. Recently, Sakurai et al. (2014) quantified the impact of the CO_2 fertilization on soybean yields in parts of the United States, Brazil, and China using a Markov Chain Monte Carlo (MCMC) parameter estimation approach. Finally, Kassie et al. (2010) investigated the impact of technological advancement (adoption of improved seeds) on crop yields and incomes in Uganda using propensity matching score on a 927 household cross-sectional database.

At the global scale, we classified the prior studies into those that investigated the impact of climate change (using Intergovernmental Panel on Climate Change [IPCC] model projections) on future crop yields and those that identified historical yield trends and their relationships with key climate variables. Parry et al. (2005), for instance, have evaluated the implications of climate change on food production using the business as usual climate scenario, stabilization scenarios and the special report on emission scenarios. They found that Africa is most at risk, and that stabilization 550 ppm would avoid most of the climate risk on food production. Rosenzweig et al. (2014), through their study using gridded crop models have examined how crops respond to climate in different latitudes and time periods and changes in atmospheric CO_2. They found strong negative effects of climate change at higher levels of warming scenarios. Fischer et al. (2005) developed an integrated ecological-economic modeling framework and used it to demonstrate that enhanced CO_2 levels in conjunction with increased temperatures and extreme events might depress global crop yields and increase production risk. A comprehensive review of the impacts of climate change on food security can be found in Schmidhuber and Tubiello (2007). In their meta-analysis, they show that the number of people at risk by 2080 ranges from 5 million to 170 million and that it strongly depends on the socioeconomic development conditions.

Other sets of studies include historical trend analyses at the global scale with or without using essential climate variables. Calderini and Slafer (1998) analyzed trends in the yield and yield stability of wheat during the 20th century for 21 countries using linear and nonlinear regression models. They found that most of the 21 countries did not show any trend in the first three to five decades and a significant increase in yields in the recent times. Ray et al. (2012) reported the trends in crop yields for maize, rice, wheat and soybeans from 1961 to 2008. They also showed that the returns have stagnated across 24%–39% of the growing regions and hence argued for new investments in underperforming areas. Both these studies mainly focused on detecting the trends in crop yields but did not evaluate the explanatory factors that lead to them. Lobell and

Field (2007) have shown that the impacts of rising temperatures on crop yields (wheat, maize, and barley) are small relative to the gains from technological advances, thereby showing the coupled nature of climate and technology in impacting global yields. Relating trends to the explanatory factors was attempted by Lobell et al. (2011) who primarily focused on understanding the changes of maize, wheat, rice, and soybean yields after 1980 as it relates to the recent changes in precipitation and temperature. Iizumi et al. (2014) presented the spatial distribution of the impacts of ENSO on the yields of wheat, maize, soybean, and rice. They noted that the overall effects of ENSO on these crops were uncertain and can be both positive and negative. Using a high-resolution crop yield dataset from 1979 to 2008, Ray et al. (2015) classified how yield variability of wheat, maize, rice, and soybean were related to either normal or extreme fluctuation in temperature and precipitation variability.

Thus, in our survey, we found that the crop yield studies were vast and disparate focusing on a specific region or the impact of a particular climate variable or technology. To our knowledge, there has not been a comprehensive global analysis of the changes in the crop yields and how they relate to different large-scale and regional climate variables, climate change variables and technology in a unified sense that also provides robust model parameter uncertainties. Hence, in contrast to all these studies, in this article, we explore how large-scale climate (ENSO), regional climate (PDSI and 500 hPa GPH anomalies), global CO_2 levels, and technology enhancements (GDP) are related to the country-level crop yields. Instead of considering just the staple crops, for each country we aggregated the annual crop yield of all the crops based on the associated harvested area (from now on we call it total crops) to account for all the crops according to their importance. We formalized them into a unified predictive model in a multilevel Bayesian framework which allows for formal uncertainty reduction and modeling.

3. Data and Preprocessing

In this section, we explain the preprocessing and the importance of the observed country-level crop yield, climate, and the nonclimatic variables.

3.1. Observed Crop Yield

Annual crop yield data from 1961 to 2013 and the associated area harvested for 160 countries is collected from the Food and Agriculture Organization of the United Nations statistical databases available at http://www.fao.org/faostat/en/#data. This data is available for most countries after 1961 with the primary exception of the countries that formed after the dissolution of the Soviet Union and Yugoslavia. For instance, crop yield data of Russia is limited to the years after 1992. Among the 160 countries, 133 countries have complete data, and 23 countries have at least 21 years of data. For each country, we compute the harvested area weighted average yield to ensure that the yield for a country is representative of the major crops harvested each year while still accounting for the minor crops.

$$Y_{it} = \frac{\sum_{k=1}^{Nc} y_{itk} a_{itk}}{\sum_{k=1}^{Nc} a_{itk}} \tag{1}$$

where t is the year (1961–2013), i is the country, k is the crop, Nc is the total number of crops harvested in year t, in country i. y_{itk} is the reported yield for a crop k in year t in country i, and a_{itk} is the corresponding harvested area.

3.2. El Niño-southern oscillation

ENSO is an interannual climate mode associated with anomalous sea surface temperature conditions in the central and eastern equatorial Pacific Ocean with warming and cooling phases. ENSO has a strong influence on the interannual variability of global precipitation and temperature (Ropelewski & Halpert, 1987), induces extreme events like droughts (Rajagopalan et al., 2000), and floods (Ward et al., 2014) and has effects on the crop production (Porter & Semenov, 2005). Here, we used the annual average NINO3.4 ENSO index obtained from Royal Netherlands Meteorological Insititute's Climate Explorer available at http://climexp.knmi.nl as an explanatory variable.

3.3. Palmer drought severity index

Droughts with varying duration, intensity, and frequency have always been a threat to food security. It is the most common cause of severe food shortages around the world, specifically in developing countries

(Dubois, 2011). Li et al. (2009) have shown that yield decrease due to droughts for major crops (wheat, maize, and rice) will rise dramatically with future climate change. Consequently, pursuing the impact of this factor on yields is of particular importance. In contrast with the past studies which examined the effect of precipitation and temperature (Lobell et al., 2011; Osborne & Wheeler, 2013; Ray et al., 2015), here we evaluate the impact of historical droughts on crop yields using PDSI. This index not only integrates precipitation and temperature, but is also highly correlated with soil moisture content (Dai et al., 2004), an important factor impacting both rainfed and irrigated crop yields (Holzman et al., 2014). PDSI has been successfully applied to quantify the severity of droughts across different climates (Wells et al., 2004). It ranges from about −10 (dry) to +10 (wet) with values below −3 representing severe to extreme drought (Dai et al., 2004). Gridded monthly self-calibrated PDSI, at 2.5° resolution, provided by the NOAA/OAR/ESRL PSD (http://www.esrl.noaa.gov/psd/), Boulder, Colorado, USA, is used here.

3.4. Geopotential height anomalies

GPH approximates the height of the pressure surface above mean sea-level in the upper atmosphere levels. Fluctuations in GPH drive the atmospheric circulation patterns that in turn impact surface temperature or precipitation variability (Knapp & Yin, 1996; Nazemosadat & Cordery, 1997; Xoplaki et al., 2000) and consequently the crop yields. Cantelaube et al. (2004) found strong teleconnections between regional GPH and wheat yield anomalies in Spain that were different from the relationships they found between yield anomalies and temperature and precipitation. Lack of any studies on the global impact of GPH on crop yields prompted us to pursue the influence of this large scale climatic pattern. Detrended anomalies of the mean monthly GPH at 500 hPa are used here. This GPH level is the most important variable describing large scale air flow (Weare, 1990). Gridded monthly GPH, at 2.5° resolution, was acquired from the same source as PDSI.

3.5. Technology Enhancement and CO_2 Enrichment, Two Crop Yield Growth Drivers

Factors like technology and economic advances, improvements in seeds, fertilizer application, using new crop varieties, better management, agricultural practices and atmospheric CO_2 enrichment can lead to increases in crop yields over time. Among these, technology improvement is considered as one of the most important factors (Lobell & Gourdji, 2012). In this study, we assume that a combination of technology enhancement and atmospheric CO_2 enrichment drives crop yield increase over time. However, technology advances are sporadic and may create some degree of uncertainty regarding their impacts (Kruse, 1999). Funds are indeed necessary to meet agricultural growth and government's decisions to boost crop yields are highly influenced by financial instrument availability. In the absence of these instruments, farmers and related agencies may not utilize more advanced technologies or implement practices to enhance agricultural efficiency. GDP per capita is the best measure of a countries' economic development (Hibbs & Olsson, 2004). There are no complete time series for the years between 1961 and 2013 for the 160 countries. Hence, we used imputed per capita GDP time series (expressed in the 2005 U.S. dollars) developed by the World Bank (James et al., 2012). We assume per capita GDP involves all the industrial and nonindustrial agricultural improvement measures for example, fertilizers, agricultural machinery, management practices, remote sensing, and so on.

During the last decades, atmospheric concentrations of CO_2 have increased substantially. Crops generally respond positively to increased atmospheric CO_2 concentration (McGrath & Lobell, 2013). The positive effect of increasing CO_2 concentration on photosynthetic rates, photorespiration, and water use efficiency is comprehensively discussed (Attavanich & McCarl, 2011; Bannayan et al., 2014; Long et al., 2006). Moreover, while there is an agreement among studies that increasing CO_2 will positively impact crop production and yield (Bannayan et al., 2014; Jaggard et al., 2010; Lobell & Gourdji, 2012; Rosenzweig & Parry, 1994), precise estimates of the future fertilization effect of CO_2 enrichment on crop yields is a controversial topic (McGrath & Lobell, 2011; McGrath & Lobell, 2013). The impact of CO_2 on crops is of such great importance that a large portion of studies assessing wheat production affected by climate change have mainly investigated the impacts of future CO_2 concentrations (Kang et al., 2009). Due to the small variation of CO_2 concentration, separation of CO_2 fertilization effects from the others is very challenging (Sakurai et al., 2014). McGrath and Lobell (2013) have noted that previous studies have made simplifying assumptions about the fertilization effect of CO_2 on crop yields. Some studies utilized free air CO_2 enrichment (FACE) experiments (Ainsworth & Long, 2005) to make a better assessment of the physiological response of crop yields to CO_2 (Tebaldi &

Lobell, 2008). Most of these studies have explored the likely future impacts of CO_2 increase on crops based on different CO_2 enrichment scenarios.Understanding the past impact of enhanced CO_2 on crop yields is also crucial (Challinor & Wheeler, 2008). Here we use CO_2 concentration at Mauna Loa (Hawaii). Some characteristics at MLO such as undisturbed air, remote location, and very little impact of human activity and vegetation has made it an ideal place for monitoring atmospheric CO_2 changes. The monthly mean of the data was acquired from https://www.esrl.noaa.gov/gmd/ccgg/trends/ and converted to the annual mean.

3.6. Mean Diurnal Temperature Range (DTR)

The DTR is the difference between the daily maximum and minimum temperature. WorldClim Global Climate Data provides the average of the DTR for the past, current and future conditions (Hijmans et al., 2005). Here the current condition, that is the average of DTR from 1960 to 1990 with 1 km resolution is used. This data is geospatially averaged for each country using ArcMap and used as a country level predictor for the parameters in the Bayesian model.

3.7. Precipitation Variability

The annual average of precipitation at the country level was obtained from the World Bank website at https://datahelpdesk.worldbank.org/knowledgebase/articles/902061-climate-data-api. We computed the coefficient of variation (CV) of precipitation using data from 1961 to 2012. CV describes the extent of variability (standard deviation) relative to the mean.

3.8. Aridity Index

Aridity index, defined as the ratio of the mean annual precipitation and mean annual potential evapotranspiration is also used as a regional predictor. The global average of aridity index from 1950 to 2000 at 1 km spatial resolution used in this study was obtained from http://www.cgiar-csi.org (Zomer et al., 2008). Using this dataset, we computed the spatial average of the aridity index for each country.

3.9. Irrigated Fraction of Croplands

The expansion of irrigation facilities is a key strategy to buffer climate variability and increase food security. Given that several countries have significant surface water irrigation and storage facilities, it is important to consider it while modeling crop yields. To account for the role of the irrigation in the model, we implement the fraction of the cropland in each country that is equipped for irrigation as an important country-level predictor that constrains the response parameters. The area equipped for irrigation is the area of the land with infrastructure to provide water for the crops. It includes areas equipped for full control irrigation, equipped lowland areas, and areas equipped for spate irrigation (Portmann et al., 2010).

3.10. Spatial Cropland Coverage and Data Superposition

The PDSI and GPH data that are used in this study cover global land areas and the whole globe, respectively. However, for each country, the PDSI and GPH were averaged on croplands. Annual time series of spatial cropland coverage was used for this purpose (Ramankutty & Foley, 1999). Here, two croplands coverage data, C_3 and C_4, at 0.5° grid spatial resolution were aggregated. The C_3 pathway, also known as the photosynthetic carbon reduction cycle, is the photosynthetic pathway most often used by plants. A complex adaptation of the C_3 pathway is the C_4 pathway, which overcomes the restriction of photorespiration (Furbank & Taylor, 1995). C_4 plants such as maize and sorghum possess a higher photosynthesis efficiency than those of C_3 plants such as rice and wheat. C_3 photosynthesis only uses the Calvin cycle and takes place inside of the chloroplast in mesophyll cells. Photosynthetic activities in C_4 plants are partitioned between mesophyll and bundle sheath cells (Wang et al., 2012).

All the variables are aggregated to the annual time series. The PDSI and GPH grids at the 2.5° resolution are superimposed on to the cropland grids at the 0.5° resolution and clipped along the cropland reference. This procedure allows us to spatially aggregate PDSI and GPH over the cropland and disregard the regions without crops. There are some small islands and territories which have historical crop data, but information about their spatial coverage of croplands are unavailable. Consequently, the final results do not contain all the global countries. The cropland coverage data is available up to 2007, assuming after 2007 the cropland coverage has not changed, results covers the time span of 1961–2013 over 160 countries. Spatial crop coverage from 2007 is shown in Figure 1 where white color refers to regions without croplands.

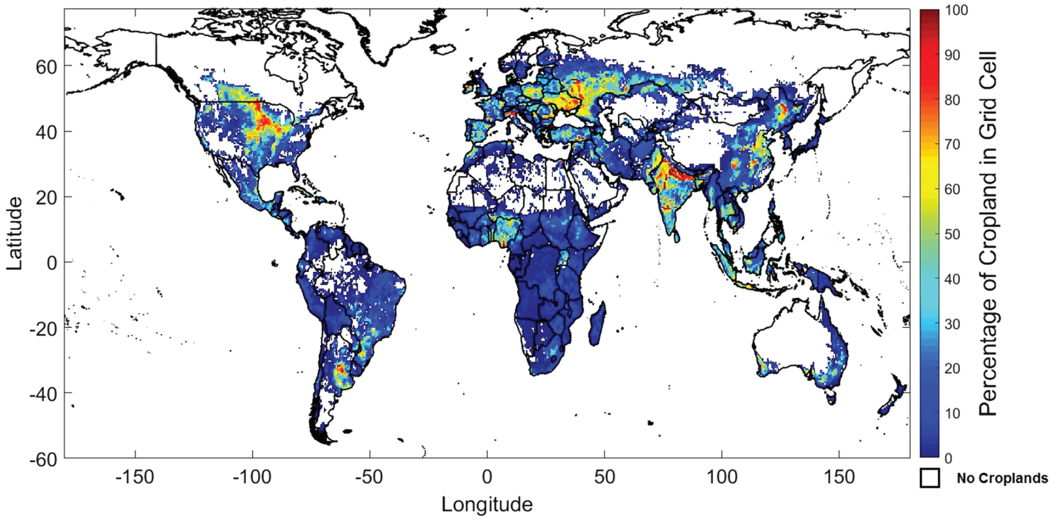

Figure 1. Spatial coverage of croplands (C_3 and C_4) in 2007.

4. Methodology

Crop growth modeling is very complex and requires extensive information that is usually incomplete and sometimes unavailable (Walker, 1989). Because of this, mathematical modeling and statistical modeling have become popular as an alternative method for many crop studies (Cai et al., 2011). A general multi-level modeling framework that allows structuring of information within and across countries was explored here using a hierarchical Bayesian model. Our goal is to estimate the distribution of crop yields in each of the 160 countries across the globe. The time series (1961–2013) of the average crop yields in each country is informed by climate covariates (ENSO, PDSI, and GPH), anthropogenic influence (global CO_2 concentration) and technology improvements (historical per capita GDP). In addition, we have climatological attributes that include aridity index, mean DTR, precipitation variability and country-level irrigation fraction as country-level predictors for ENSO and CO_2 influence coefficients. A particular climate predictor may inform the crop yield at each of the countries. However, the response across the countries may vary systematically due to local conditions. The multilevel model can be used for structuring this information (within and across countries), by considering multiple levels of modeling. The individual regression coefficients for each country on each climate predictor are estimated at the first level. The second level informs these regression coefficients across countries using local features - the aridity index, mean DTR, variability of precipitation and irrigation fraction. This procedure allows us to simultaneously parameterize the variations in the response of yield to climate predictors across countries.

The crop yield **Y** are assumed to come from a distribution (process model) with a probability density function $f(Y|\theta)$, where θ is the parameter vector. In the current application, we consider that log(**Y**) is normally distributed. This assumption was checked using Kolmogorov-Smirnov test on the log-transformed data. The first level of the model considers that in each country i, $\log(Y_{it})$ is described by a Normal distribution with time varying mean μ_{it} that is informed by a regression on the five chosen covariates with intercepts α_i and a (5×160) regression coefficient matrix $\boldsymbol{\beta}$. The second level of the model considers that the regression coefficients for ENSO and CO_2 can be estimated using country level predictors. This structure allows parameterizing the response to a particular climate covariate across countries that may have a diverse range or scale of values. The errors from the regression model are considered to be independent and identical with a 0 mean and a variance that is estimated as part of the model.

$$\log\left(Y_{it}\right) \sim N\left(\mu_{it}, \sigma_i^2\right) \tag{2}$$

$$\mu_{it} = \alpha^i + \beta_1^i\left(GDP_{it}\right) + \beta_2^i \log\left(CO_2\right)_t + \beta_3^i ENSO_t + \beta_4^i PDSI_{it} + \beta_5^i GPH_{it} \tag{3}$$

$$\beta_2^i \sim N\left(a_1 + b_{11}CV_i + b_{12}DTR_i + b_{13}\gamma_i + b_{14}IF_i, \sigma^2_{\beta_2}\right) \quad (4)$$

$$\beta_3^i \sim N\left(a_2 + b_{21}CV_i + b_{22}DTR_i + b_{23}\gamma_i + b_{24}IF_i, \sigma^2_{\beta_3}\right) \quad (5)$$

where Y_{it} is the average yield in year t in country i, CV_i, DTR_i, γ_i, and IF_i are the coefficient of variability of annual rainfall, average DTR, the aridity index and the fraction of croplands under irrigation of the country i. Since the effect of the ENSO and CO_2 are at the larger spatial scales impacting many countries, the second level helps pool this information by constraining the response parameter using the regional characteristics (Armal et al., 2018; Renard et al., 2013). The errors with variance $\sigma^2_{\beta_2}$, and $\sigma^2_{\beta_3}$ represent variation in the ENSO and CO_2 coefficients between countries beyond what is explained by the aridity index, DTR, variability of precipitation and irrigation fraction.

The joint posterior distribution $p(\theta|\text{data})$, of the complete parameter vector is derived by combining the prior distributions and the likelihood functions. We assumed a uniform prior distribution for the variance terms and uninformative normal priors for the coefficients of the second level (Gelman, 2006b). The parameters are estimated using JAGS (Denwood, 2016; Plummer, 2012). JAGS (Just Another Gibbs Sampler) is a program for the analysis of Bayesian models which employs the Gibbs sampler, a MCMC method for simulating the posterior probability distribution of the parameters conditional on the current choice of parameters and the data. Four parallel chains are simulated using random initial values for the parameters. Each chain was run for 15,000 iterations with 70% burn-in to discard the initial estimations. As Gelman and Rubin (1992) recommended, we monitor the convergence using a shrink factor. The ratio of variance between the chains and variance within the chains should be lower than 1.1.

5. Results and Analysis

5.1. Model Verification

Initially, we evaluated the fit of the Bayesian multilevel model using posterior predictive checks (Rubin, 1984). The accuracy of the predictions is measured using the Deviance Information Criterion (DIC) (Spiegelhalter et al., 2002). The DIC is based on the posterior distribution of the deviance statistic $D(\theta) = -2\log f(y|\theta) + 2pD$, where $f(y|\theta)$ is known as the "likelihood function," which is mathematically the conditional density function of the predictand y given the parameters in vector θ, and pD is the effective number of parameters.

In Figure 2a, we present the variance explained (adjusted R^2) from the model for each of the 160 countries. We can see from the figure that the amount of variance explained is greater than 60% in most of the countries. A few exceptions (with lower than 25% adjusted R^2) include the former Soviet nations Slovakia, Luxembourg, Lithuania, Czech Republic, Estonia, and Eritrea among others. The countries in Africa and South America that have low adjusted R^2 have had periodic civil unrests and geopolitical conflicts. Therefore, the data on yields and GDP may not be indicative of the trend and variability.

Since much of the variance explained is a result of the monotonic trend in the yield explained by the monotonic trend in the CO_2 and GDP, we also present, in Figure 2b, the adjusted R^2 from the model after correcting for this trend. We remove the trend causing terms ($\alpha^i + \beta_1^i GDP_{it} + \beta_2^i CO_{2t}$) from both observed and model predicted yields, and then compute the adjusted R^2 of the residuals. This detrended version will reflect the amount of variance in the observed yield data that is explained by the remaining terms, ENSO, PDSI, and GPH. We can see that while in most of the countries we can explain up to 20% of the residual variance using the climate covariates, in some countries like Australia, Argentina, Bolivia, Peru, Myanmar, the Russian Federation, South Africa, and Spain, we can explain up to 40% of the residual variance. In a few countries (not very visible on the map due to scale) such as Armenia, Moldova, Croatia, Serbia, and Montenegro, we see adjusted R^2 from 47% to 78%. List of the countries that have atleast 30% residual adjusted R^2 are presented in Table 1. Together, we can see that based on the choice of the explanatory variables that include both monotonic change and natural variability, we were able to explain much of the variations in the global crop yields.

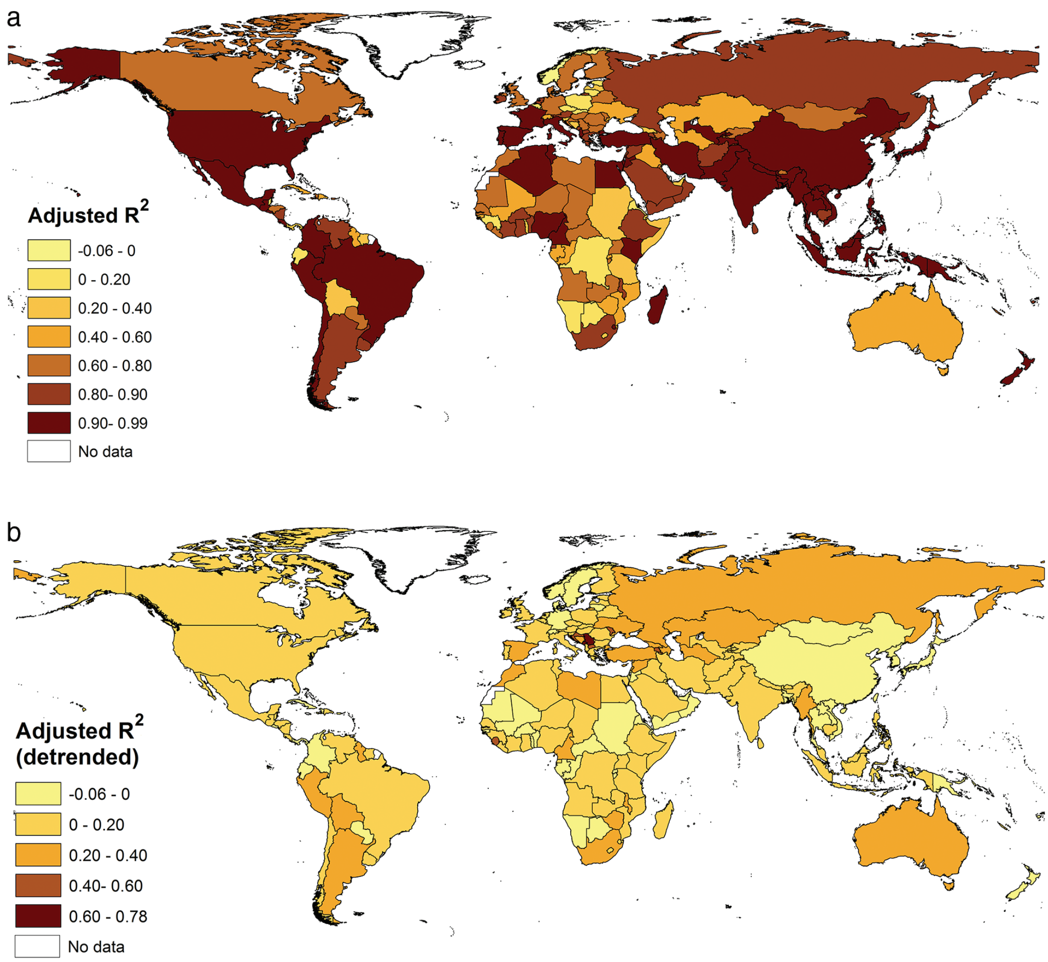

Figure 2. Adjusted R^2 from the model based on (a) all predictors and (b) predictors after removing CO_2 and GDP per capita.

5.2. Inference Based on the Regression Coefficients

The median of the posterior probability distribution of the regression coefficients for GDP (β_1^i) and CO_2 (β_2^i) for the 160 countries are shown in Figure 3. Countries where $p(\beta > 0) > 0.9$ or $p(\beta > 0) < 0.1$ are shown in thick blue border. These are the countries that have strong positive or negative relationship with the explanatory variable (GDP in Figure 3a and CO_2 in Figure 3b). The value of the green colors indicates the strength of the positive relationships, that is, the sensitivity expressed as change in the yield (log scale) per unit change in GDP or CO_2 (log scale). Similarly, orange and red colors indicate the strength of the negative relationships. Out of the 160 countries, 101 (20) countries show a statistically significant positive (negative) relationship with GDP. Similarly, 93 (23) countries show a statistically significant positive (negative) relationship with CO_2. These results also corroborate what we find in Figure 2a where much of the variance can be explained using the monotonic trend coefficients β_1^i and β_2^i. Among the 160 countries, 54 countries have a significant positive relationship with both GDP and CO_2. The United States, Denmark, Germany, Spain, Mexico, Portugal, and Philippines are among these. Furthermore, given their high correlation, we expect some GDP (β_1^i) and CO_2 (β_2^i) coefficients to be negatively correlated, that is, the resulting regression coefficients for each of them may not be unique. We see this, for example, in Brazil, India, China, Uruguay, Sudan, and some European nations.

Among the second level model coefficients for β_2^i, that is, the response coefficient for CO_2 (equation 4), we find that b_{11}, b_{12}, and b_{14} are statistically significant. This indicates that the CO_2 regression coefficients can be related to country-level CV, DTR, and the irrigation fraction IF. In Figure 4, we present the pairwise relations of the CO_2 median regression coefficients that are statistically significant (countries with blue boundaries) with the country-level predictors. The size of the circle indicates the GDP per capita of the country in 2013;

Table 1.
List of the Countries That Have Atleast 30% Residual Adjusted R^2 *After Removing* CO_2 *and GDP Per Capita*

	Adjusted R^2 considering the whole variables	Adjusted R^2 after detrending
Montenegro	0.81	0.79
Serbia	0.63	0.65
Croatia	0.62	0.52
Moldova	0.66	0.50
Armenia	0.89	0.48
Macedonia	0.89	0.44
Sierra Leone	0.69	0.42
Russia	0.82	0.39
Syria	0.81	0.38
Morocco	0.79	0.37
Argentina	0.86	0.37
Georgia	0.29	0.37
Bosnia and Herzegovina	0.37	0.36
Spain	0.94	0.35
Azerbaijan	0.75	0.34
Bolivia	0.35	0.34
Cameroon	0.96	0.31

larger circles indicate countries with a high GDP. Based on the posterior distribution of b_{11}, we find there is a general negative trend, pointing out that the countries with larger CV of precipitation have a lower CO_2 response and vice versa. From Figure 4a, we can see that countries with high GDP (larger circles) have a smaller CO_2 response regardless of their CV of precipitation. Countries with low GDP (smaller circles) have greater CO_2 response factors, again across the spectrum of CV. An interesting observation one can uncover from this phenomena is that the response of CO_2, that is, the impact of CO_2 on crop yields is greater for low GDP countries. High GDP countries typically have greater yields due to better agricultural practices and infrastructure including the access to irrigation, better seeds, and fertilizers. Hence, the impact of CO_2 enhancement is seldom seen. To the contrary, low GDP countries, have had lower yields historically due to their poor access to technology; increases in the CO_2 levels have contributed to a sustained upward trend in yields over time.

Figure 4b, the pairwise relationship between DTR and the median of the CO_2 regression coefficient, also reveals some interesting trends. There is a positive relationship between DTR and the CO_2 response coefficient. The higher the DTR, the greater the CO_2 response. DTR is an indicator of the energy available for crop growth through the day. We find that the countries with higher DTR better respond to CO_2 enhancement in the atmosphere especially for the low GDP countries. Rosenzweig and Tubiello (1996), in their model studies on wheat, have seen that the negative effects of temperature are reduced when the minimum temperature increases more than the maximum temperature. They also showed that under current CO_2 concentrations, the yields responded negatively to temperature changes, however, the response was both positive and negative (depending on the region) under elevated CO_2 levels. Herein, we reiterate that we are only showing that countries with greater DTR on average respond positively to CO_2 enhancements. b_{13}, the second level coefficient that relates the CO_2 response parameter β_2^i with the aridity index of the country is not statistically significant. This can be seen from Figure 4c. Finally, in Figure 4d, we present the relationship between the country-level irrigation fraction with the CO_2 coefficient β_2^i. There is a general positive trend, that is, countries with greater irrigation capacity have a much larger positive CO_2 coefficient, indicating that the positive impact of CO_2 enhancement on the crop yields is greater for countries with greater irrigation facilities. The combined effect of enhanced atmosperic CO_2 and improved irrigation that buffers climate variability is a net positive on the countries' aggregate crop yields. For readers reference, we provide the maps for the country-level CV, DTR, aridity index, irrigation fraction and per capita GDP of 2013 in Figure 5.

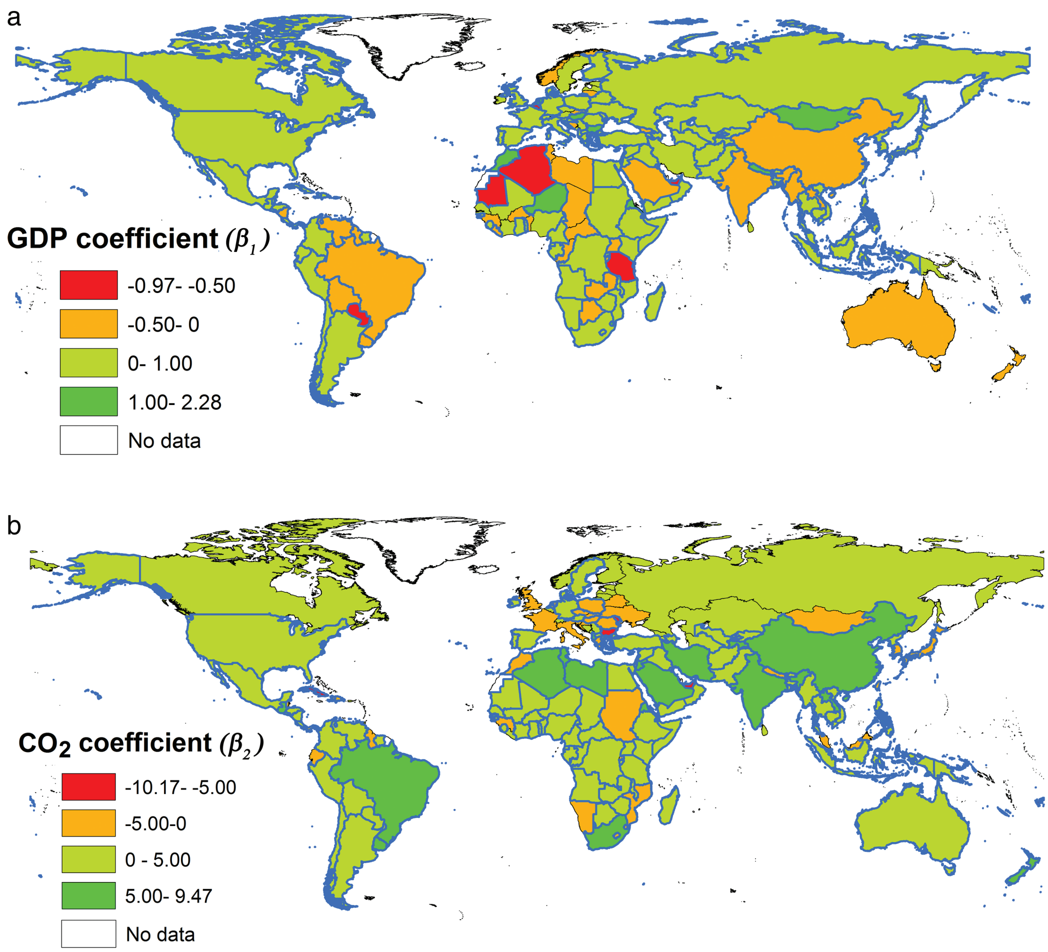

Figure 3. The median of the posterior probability distribution of the regression coefficients for (a) GDP per capita and (b) CO_2.

The median of the posterior probability distribution of the regression coefficients for PDSI (β_4^i), GPH (β_5^i), and ENSO (β_3^i) for the 160 countries are shown in Figure 6. As in Figure 3, the countries where $p(\beta > 0) > 0.9$ or $p(\beta > 0) < 0.1$ are shown in thick blue border and these countries have strong positive or negative relationship with the predictor (PDSI in Figure 6a, GPH in Figure 6b and ENSO in Figure 6c). Out of the 160 countries, 43 (17) countries show a statistically significant positive (negative) relationship with PDSI. 40 (25) countries show a statistically significant positive (negative) relationship with GPH. A total of 3 out of the 160 countries show a statistically significant positive relationship with ENSO. Much of the natural variability signal could be captured using the PDSI and GPH co-variates, thereby rendering ENSO's influence insignificant.

The United States, Canada, several countries in South America, Eastern European countries, Australia, Middle East, and Southeast Asian countries are the ones that have significant PDSI coefficient. Furthermore, we find that Serbia, Croatia, Moldova, Macedonia, and Sierra Leone are among the countries that have a statistically significance PDSI coefficient along with having residual adjusted R^2 greater than 40%. We find a significant GPH association in the southeast Asian countries, especially around the equator, Eastern Europe, Russia, and the southern and sub-Saharan African countries. The historical crop yields of Croatia, Moldova, and Sierra Leone have a statistically significant connection with PDSI and GPH and their multilevel linear model fit exhibited high residual adjusted R^2. The historical yields of Montenegro and Armenia also showed a significant connection with GPH and have high residual adjusted R^2 in the model, but did not correlate well with PDSI.

In Figure 7, we present the relationship between PDSI (Figure 7a) and GPH (Figure 7b) median regression coefficients and the aridity index of the associated countries. As in Figure 4, the size of the circle indicates the GDP per capita of 2013 of the country. Larger circles represent countries with higher GDP. Only countries

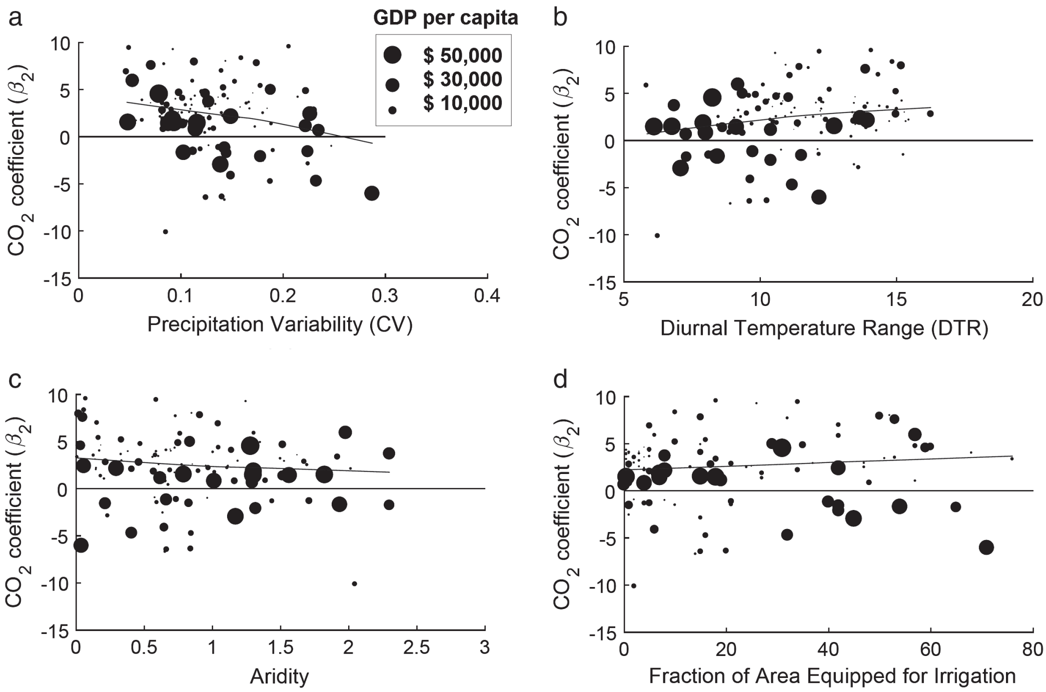

Figure 4. (a) Relationship of median regression coefficients of CO_2 for statistically significant countries versus associated precipitation variability. Size of the circles demonstrates the GDP per capita of the countries; A locally weighted scatterplot smoothing (LOWESS) is used to show the negative relationship between CO_2 coefficients and precipitation variability (the gray line); (b) median regression coefficients of CO_2 for statistically significant countries versus associated diurnal temperature range (DTR). A positive relationship between CO_2 coefficients and DTR is seen; (c) median regression coefficients of CO_2 for statistically significant countries versus associated aridity; not a strong relationship between CO_2 coefficients and DTR was found; (d) median regression coefficients of CO_2 for statistically significant countries versus associated DTR. A positive relationship between CO_2 coefficients and IF is seen.

that have a statistically significant PDSI or GPH coefficient (countries with blue boundaries) are shown. From Figure 7a, we can see that there is a negative trend; countries with larger aridity index (wetter countries on average) have a negative PDSI response and countries with smaller aridity index (dryer countries) have a positive PDSI response. The aridity index map (Figure 5c) indicates that the wet countries are dominant in southeast Asia, western Europe, and South America. These countries exhibit a negative PDSI response indicating that high annual PDSI leads to lower yields. A high PDSI in wet countries is indicative of more than average rainfall years; because high PDSI values may imply floods (Li et al., 2009), this could lead to crop damage. Wittrock et al. (2011) have reported this phenomenon for Canada recently. On the contrary, the dry countries have a positive PDSI response, indicating that high PDSI (more rainfall) leads to an enhanced crop yield. Unlike CO_2, which is a long-term effect, the influence of GDP is not apparent in PDSI. A similar pattern was observed for GPH.

5.3. Out-Of-Sample Predictive Performance

Validation of the model for an out-of-sample block can reveal the true performance of the multilevel Bayesian model. It can also serve as a test for using the model based on future climate, CO_2 and GDP per capita projections. We evaluate the model using the split sampling technique. The first 40 years (1961–2000) are used to develop the Bayesian model which is in turn used to predict the yields for the left out 13 years (2001–2013). We evaluated the model performance using average ignorance score (IG), otherwise known as the log-likelihood score. IG is a useful measure for evaluating probabilistic forecasts since it generalizes the categorical forecasts beyond the binary case (Roulston & Smith, 2002) and is sensitive to both the mean and variance of the predicted distribution. We computed the average IG for each country for the out-of-sample predictions using the easyVerification package available in the open source software R (https://cran.r-project.org/web/packages/easy Verification/easyVerification.pdf). We use tercile categories for evaluating the IG. The out of sample predictions are considered to be useful if IG of predictions is lesser than the IG of climatology. For the tercile categories, the average IG of climatology is 1.585 (log 2(3), 3 being the number of categories).

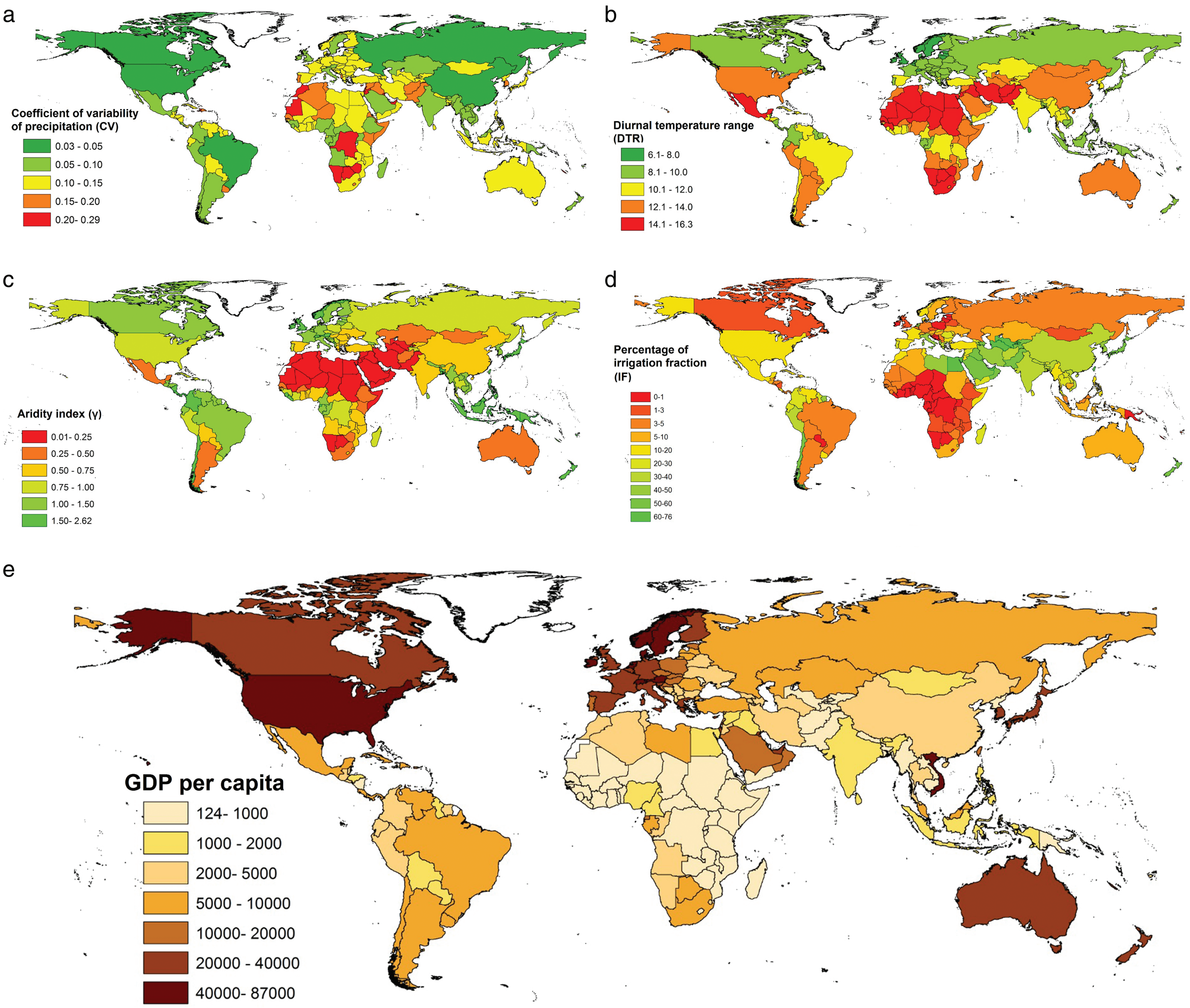

Figure 5. (a) Global map of precipitation variability from 1961 to 2012, (b) global map of mean diurnal temperature range from 1960 to 1990, (c) global map of mean aridity spanning 1950–2000, (d) global map of fraction of cropland areas equipped for irrigation, (e) GDP per capita in 2013.

In Figure 8a, we present the average IG for the 133 countries (with complete data records) used for out of sample predictions. We also present the time series of the observed yields and distribution of the predicted yield for four countries, the United States, Indonesia, Afghanistan, and Fiji in Figures 8b–8e. Training period (validation) observations are shown using the red (green) line. A total of 85 countries of the 133 countries used for this demonstration have an average IG less than the climatological IG. These include the United States, China, Southeast Asian countries, Brazil, and southern African countries among others. Venezuela, Uruguay, Namibia, and Colombia are among the countries with high average IG. The time series plots shown as an example reveal that the interquartile range of the predicted yields captures the observations most times. The general trend, increasing in the case of the United States and Indonesia; decreasing in the case of Fiji, and jump change in the case of Afghanistan, is also captured well. Given its ability to capture the trends in crop yields, this model can serve as a handy supplement to the crop physiology-based models that attempt to predict future yields under prescribed "business as usual" mode for changes in the values of the predictors. However, predicting future yields may be associated with a larger uncertainty due to potential extrapolation of the fitted data.

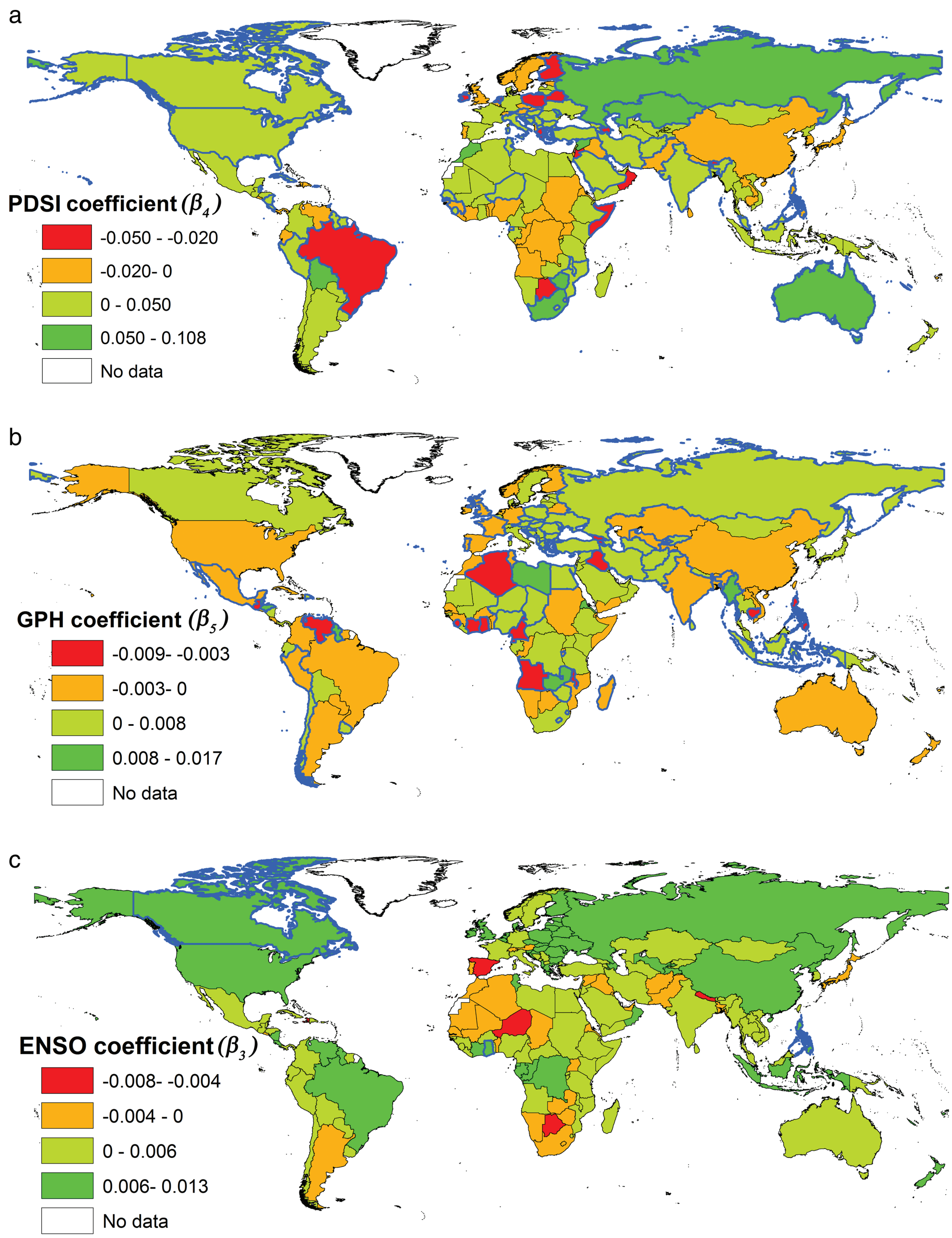

Figure 6. The median of the posterior probability distribution of the regression coefficients for (a) PDSI, (b) GPH, and (c) ENSO.

6. Discussion and Summary

There are currently over 7.3 billion people in the world, with an expected population of over 8.5 billion by 2030 and 9.7 billion in 2050. Increased demand for food due to population, income growth, changes in global food consumption patterns and increasing demand for bioenergy will raise pressure for increased and more sustainable agricultural production. It is projected that food production has to double in the coming decades to keep up with increasing demand (Tilman et al., 2011). During the recent decades, along with the fast changes in human life, the agricultural sector has improved tremendously. Changes in the agricultural sector will continue to happen in the future. Hence, we should expand our knowledge regarding the

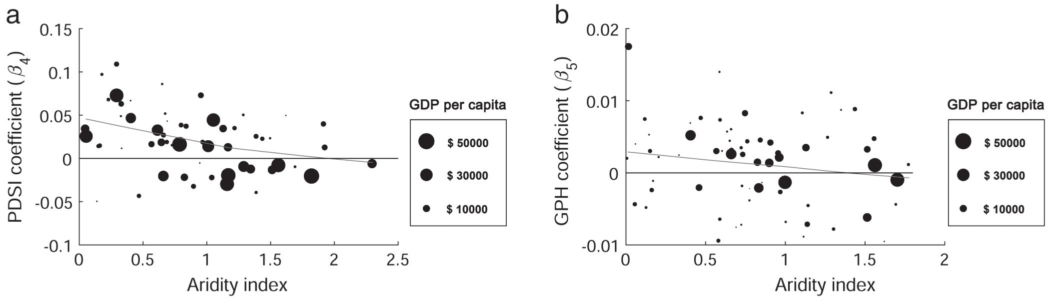

Figure 7. (a) Relationship between PDSI coefficients and the aridity index for statistically significant countries. (b) Relationship between GPH coefficients and the aridity index for statistically significant countries; in both scatter plots, the size of the circles demonstrate the GDP per capita of the countries. A locally weighted scatterplot smoothing (LOWESS) is used to show the trend.

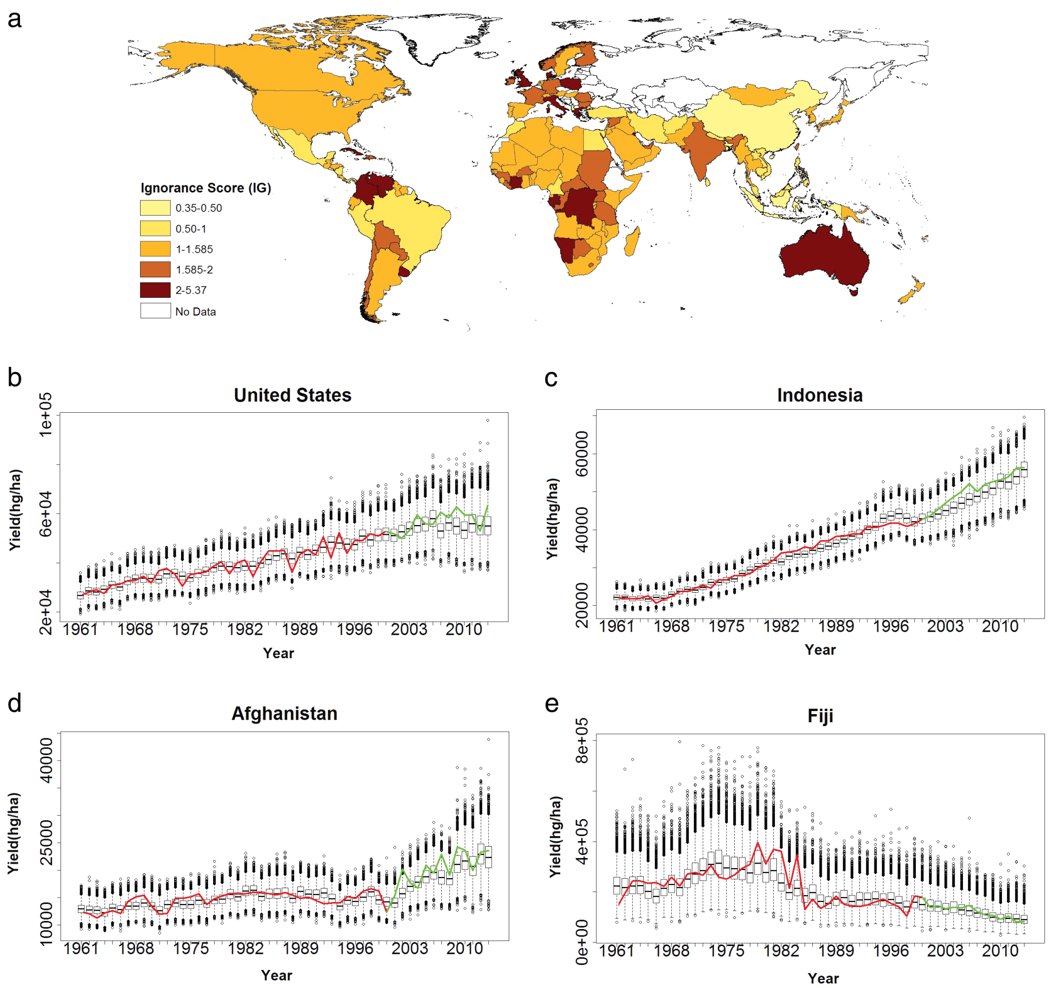

Figure 8. (a) Ignorance score of 133 countries with complete data from 1961 to 2013; and cross validation through removing observation data from 1961 to 2000 for (b) United States; (c) Indonesia; (d) Afghanistan, and (e) Fiji.

drivers of these changes to be able to propose more effective strategies for food security. Moreover, during the last two decades, global croplands remained fairly stable (http://data.worldbank.org/indicator). It may be implied that in many countries, the land area used for agriculture has reached its maximum limits, so any possibility for increased food production needs to consider increase of agricultural yields. There is a clear and urgent need to unravel the factors that affect crop yields more than the past. Understanding the change in crop yields is also important for policy makers in designing the farm programs, disaster relief legislation, research investments and climate-related adaptation/mitigations measures. It can provide a guideline for future agricultural research planning and it can be used to evaluate the returns on agricultural research. Accordingly, we attempted to develop an inference/predictive model that enables a good understanding of the changes in crop yields along with providing the ability to predict the yields given current or future conditions. It captures the past impacts of climate variables and technology on crop yields and can be used to evaluate future climate- related yield variability and address alternate factors contributing to the spatial heterogeneity in climate-yield response.

In this article, we explored the connection between crop yields, technology improvement and several global and regional scale climatic indicators at the country scale from 1961 to 2013. Most of the similar global studies that addressed the effect of climate on crops, focused on precipitation and temperature, while considering a few staple crops such as wheat, maize, and rice. In this study, we considered the weighted average of all the crop yields, emphasizing on the most important crops in each country based on the associated harvested area. We used partial pooling through hierarchical Bayesian modeling to reduce uncertainties associated with coefficient estimation of the variables for ENSO and atmospheric CO_2 enrichment. Monotonic trend of crop yields for most of the countries were explained by the monotonic trend in the CO_2 and GDP per capita variables. Although, irrigation substantially decreases the impact of climate variables, the model found significant connections between yields fluctuation and climate for many countries. Climate predictors explained 20% to more than 70% of the residual variance for most of the countries. While a negative relationship between crop yields and PDSI existed in a few countries, the relationship was generally positive. It was shown that across the spectrum of CV (low variation to high variation countries), countries with high GDP per capita have a smaller CO_2 response and vice versa. Furthermore, countries with higher DTR better respond to atmospheric CO_2 enrichment especially for the low GDP countries. We realized that wetter countries have a negative PDSI response and countries with smaller aridity index have a positive PDSI response. Countries with better irrigation facilities have a much positive influence of CO_2.The model performs well under out-of-sample verification. The main limitation of our study is its inability to capture crop yields' responses to variables at subnational levels. However, doing this would be difficult because of the lack of high resolution crop data for most places except at field research sites. Furthermore, several countries which are based on irrigated agriculture do not properly account its groundwater usage. While we are using the country-level irrigation fraction as a proxy, it has to be noted that it comes with certain level of uncertainty. We also acknowledge that the model co-variates are selected based on known influences and prior correlation analyses. Full causality and nonlinear interactions have not been tested here.

Consequence management of future climate-driven factors that adversely affect crop yields can be optimized (Afshar & Najafi, 2014) and highlighted by understanding the relationships between crop yields and climate patterns. This will enable us to evaluate alternative food policy strategies and taking precautionary economic measures. Additionally, countries can cope with negative impacts of climate through some measures like fertilizer, changing crop type, and planting date (Tubiello et al., 2007). A comprehensive study is indeed required to recognize the most vulnerable crops in each country. The results of such a study would be helpful for countries that are dependent on agricultural imports. The degree of impact of CO_2 enrichment on the agriculture and crops has always been a controversial topic of debate. Expanding knowledge in this sector as well as using more precise data with higher resolution like satellite based data of Orbiting Carbon Observatory-2 mission (Frankenberg et al., 2014) can provide useful insights for this problem. There is a strong agreement among many reports about the impact of climate change on crop yields and crop productions in the future. Most of them unanimously agree that the future impact of climate change on food security does not seem promising. However, most parts of the world likely will be able to continue to feed itself in the coming decades (Parry et al., 2004). More research and investments in crop enhancement, and climate change adaptation policies will help sustain crop yield growths in the future (Lobell & Gourdji, 2012).

In the era of climate change that is inducing more frequent weather extremes, crops are becoming more vulnerable. Furthermore, geographical locations of food production are becoming more and more distant from geographical locations of food consumption in many cases (Fader et al., 2013) and other factors like burgeoning population, political issues, and expensive energy shortages are undermining food security around the world. Thus, understanding the current and past dynamics and connections across the climate-water-energy nexus is essential, as the many countries try to manage the consequences of climatic and nonclimatic variables on crops. Our work tries to enhance the knowledge of global food security field, which is of relevance to policy initiatives, decision makers, water and energy managers, government and nongovernment organizations like U.S. Department of Agriculture (USDA) and Food and Agricultural Organization of United Nations (FAO), stakeholders and scientists with similar interests to ours. Our ongoing work in this direction is focused on creating novel ideas of modeling and optimization techniques for ensuring global food security.

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