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Characterizing agricultural impacts of recent large-scale US droughts and changing technology and management

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ABSTRACT

Process-based agricultural models, applied in novel ways, can reproduce historical crop yield anomalies in the US, with median absolute deviation from observations of 6.7% at national-level and 11% at state-level. In seasons for which drought is the overriding factor, performance is further improved. Historical counterfactual scenarios for the 1988 and 2012 droughts show that changes in agricultural technologies and management have reduced system-level drought sensitivity in US maize production by about 25% in the intervening years. Finally, we estimate the economic costs of the two droughts in terms of insured and uninsured crop losses in each US county (for a total, adjusted for inflation, of $9 billion in 1988 and $21.6 billion in 2012). We compare these with cost estimates from the counterfactual scenarios and with crop indemnity data where available. Model-based measures are capable of accurately reproducing the direct agro-economic losses associated with extreme drought and can be used to characterize and compare events that occurred under very different conditions. This work suggests new approaches to modeling, monitoring, forecasting, and evaluating drought impacts on agriculture, as well as evaluating technological changes to inform adaptation strategies for future climate change and extreme events.

1. Introduction

Drought and heat events accounted for 12% of all billion-dollar US disasters from 1980 to 2011, but almost 25% of total monetary damages (FEMA, 1995; NCDC, 2012; Smith and Katz, 2013). The 1988 US drought is estimated to have cost the country $40 billion ($79 billion in 2013 dollars), behind only Hurricane Katrina in 2005 ($149 billion 2013 dollars) as the most costly US weather-related disaster (NCDC, 2012; Riebsame et al., 1991). Warming temperatures and shifting precipitation patterns may increase the frequency and severity of large-scale droughts in important agricultural regions (Sheffield and Wood, 2008; Solomon, 2007; Wehner et al., 2011). Recent work suggests that extended drought will harm more people in the future than any other climate-related impact, specifically in the area of food security (Romm, 2011).

Almost 40% (about $30 billion adjusted for inflation) of the cost of the 1988 drought is estimated to have come from direct losses to agricultural production (Smith and Katz, 2013). Preliminary estimates for the cost of the 2012 US drought based on direct crop losses alone are almost $30 billion (NCDC, 2012), and direct losses to livestock and dairy likely added another $5 billion. Once full direct and indirect estimates are available, 2012 is expected to rival or even surpass 1988 in terms of economic consequences.

For decades, agricultural scientists have developed models for evaluating the effects of weather on crops and productivity at the farm scale (e.g., DSSAT Jones et al., 2003, EPIC Williams et al., 1995, and APSIM McCown et al., 1996). These process-based models of crop growth and development can provide insight into the impacts of drought and other plant stressors (Porter and Semenov, 2005; Semenov and Porter, 1995). In the last decade, researchers have extended these tools to evaluate productivity at regional and global scales (Elliott et al., 2013, 2014b; Glotter et al., 2014; Izaurralde et al., 2006; Nelson et al.,

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2009) and applied them in multi-decadal multi-model assessments of climate change impacts (Rosenzweig et al., 2014). CERES-Maize (the primary maize model used in DSSAT and in this study) has been applied with two different ET estimation methods to reproduce the results of a field trial in Colorado. The model was found to be able to reproduce ET, grain yield, biomass, and soil moisture under various levels or irrigation in a semi-arid region (Anothai et al., 2013). At large scales, the effect of the number of rainy days in highly water limited settings has been considered in the context comparison of different gridded historical climate data products (Glotter et al., 2014). Large-scale extreme drought was recently evaluated using similar models and data to those used here, in the context of the possiblity of a new "Dust Bowl" type event in the early 21st century (Glotter and Elliott, 2016).

This study investigates (i) whether crop models can reproduce the observed impacts of past extreme events on agricultural production at various scales; (ii) to what extent they can reliably predict the impacts of forecasted or emerging meteorological events to improve lead times for response planning; (iii) to what extent changes in farm technology and management over decadal time-scales can affect system-level sensitivity to climate extremes; and (iv) how data and models can be used to improve assessments of the economic impacts of agricultural drought and comparisons of drought events separated by decades. US maize production over the last several decades provides the context for exploring these questions because of the meteorological intensity of recent droughts across the US Corn Belt states, documented technological and management changes in the sector over this period, and the quality and quantity of long time-series weather- and crop-related data.

2. Material and methods

2.1. Model assumptions and parameterizations

We simulate maize growth and yield using the field-scale CERES-Maize model, part of the Decision Support System for Agrotechnology Transfer (DSSAT Jones et al., 2003; Hoogenboom et al., 2010 for latest DSSAT release), at 10 km resolution for the conterminous US using the parallel System for Integrating Impact Models and Sectors (pSIMS Elliott et al., 2014b). The model is used in three distinct modes of study. To investigate our ability to reproduce past events, we performed hindcasts of 1979–2011 maize yields. To investigate our ability to predict the impacts of emerging meteorological events, we simulated 2012 US maize production before official statistics were released in February 2013 (Elliott et al., 2013). To investigate the effect of changes in agricultural technologies on the system-level drought sensitivity of commercial maize production, we analyzed the 1988 and 2012 droughts using historical counterfactuals (1988 weather with 2012 technology and practices, and vice versa). In all modes we evaluated the ability of the crop model system to reproduce observed drought impacts at various scales by comparing simulated yields with USDA NASS survey data at state and national levels. In so doing, we enhance understanding of the validity of climate change impact assessments based on dynamic process-based crop models (Rosenzweig et al., 2014).

Simulations for rainfed and irrigated maize were driven by weather data up to and including November 30, 2012, considering the following management practices and trends:

- **Planting date**: We simulated five distinct planting dates each year, the dates at which 10, 30, 50, 70 and 90% of the crop were reported to be planted based on state- and Crop Reporting District (CRD)-level crop progress data (National Agricultural Statistics Service, 1995-2013). These outputs were equally weighted in the aggregated results.
- **Relative maturity (RM) group**: To reflect the fact that seed-choice decisions are made based on local recent environmental conditions, the relative maturity (RM) group of the chosen cultivar is determined separately in each five-year period and for each planting date. The decision is made by estimating the optimal RM over the preceding 5-year period using the local history of growing degree units accumulated between the planned planting and assumed maturity day.
- **Planting density**: Based on state level crop progress data from 1979 to 2012.

Simulations also include genetic yield improvement trends parameterized based on literature and on discussions with academic and industry experts in modeling and breeding:

- **Kernel number** was increased linearly by 9% over the simulation period from 1979 to 2012 (Echarte et al., 2013) and
- **Radiation use efficiency** was increased linearly by 10% over the simulation period. This increase was estimated through discussions with breeders and crop experts to represent the fact that more recent maize hybrids have stay-green characteristics (which increase late season dry matter accumulation, i.e. RUE) and also have more upright leaves allowing for higher plant population without reduced per-plant RUE (upright leaf angle would thus increase average RUE) (Tollenaar and Lee, 2006). CERES-Maize does not facilitate direct modeling of stay-green or upright leaf angle, so RUE increases were used to mimic these factors.

Finally we considered two land-use change adaptations in post processing (both calibrated with NASS data):

- Amount of **cultivated corn area** in each county from 1979 to 2012 and
- Fraction of that area that is **irrigated** vs. rainfed.

Simulations were run with input data at a variety of spatial and temporal scales including:

- Daily time-series of key weather variables spanning January 1, 1979 to November 30, 2012, from the North American Regional Reanalysis (Mesinger et al., 2006);
- Soil profile parameters (including most notably the average soil textures, bulk density, organic carbon content, and water holding characteristics at various depth layers along with the surface drainage and runoff characteristics) were estimated from the Harmonized World Soils Database (Nachtergaele et al., 2008);
- Observed planting and maturity dates and planting densities from the USDA crop progress reports released weekly during the growing season for many decades, generally at the resolution of states or CRDs (National Agricultural Statistics Service, 1995-2013),
- County-level data from 1979 to 2011 on irrigated and rainfed harvested areas from USDA NASS; and
- Estimates of sub-county distribution of land and management practices from the Spatial Production and Allocation Model (SPAM) dataset (You and Wood, 2006).

CERES-Maize does not include dynamic functions for pests, disease, or ozone damage. For nutrient stresses, we consider here only nitrogen stress and thus nitrogen fertilizers, ignoring phosphorus and potassium. Since maize in the US is almost uniformly grown with high levels of fertilizers, we do not expect that nutrient limitations are a large factor.

2.2. Aggregation, statistical correction, and validation

We aggregate raw simulation output to the county level and compare against survey data from USDA NASS (with linear trends removed) to correct statistical biases and estimate forecast errors. Despite the fact that we include time-varying technology and management factors that reproduce a significant portion of the trend in yields, the goal in considering these empirical and semi-empirical technology and