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Rainfed maize yield response to management and climate covariability at large spatial scales

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ABSTRACT

Statistical analyses of yield and climate data across large spatial scales are an important method for exploring crop sensitivity to a variable and changing climate. However, a variety of issues complicate the interpretation of climate impacts on yield, including spatial and temporal collinearity among climate variables and between climate and management variables, as well as complex responses of yield to interactions among climate variables across different growth development phases. All of these issues, if unaccounted for, can compromise yield projections under climate change. In this study, we present a series of nested models to analyze rainfed maize (*Zea mays* L.) yield response to climate (temperature, precipitation, solar radiation) at specific growth-development phases and under different crop management practices. The models, fit using elastic net regression to address collinearity, indicate that spatial gradients in management, which occur at the same scale as climate variability, explain the majority of location-based and total yield variance. Coefficient estimates of yield responses to high temperature/low precipitation conditions during key growth development phases are consistent with reported physiological responses of maize, but only when interaction terms are included between temperature and precipitation. Yield responses to temperature and solar radiation are also modified by prior temperature regime. Overall, failure to parameterize management practices and interactions between temperature and precipitation leads to systemic errors in models linking maize yields to climate impacts at large spatial scales, both under current and projected climate.

1. Introduction

Maize is the leading cereal crop produced globally (USDA FAS, 2017) and demand is expected to increase by up to 50% in the coming century (Rosegrant et al., 2009). During the same period, mean annual temperatures are expected to increase by 3.1–4.7 °C in the Midwest U.S. (Walsh et al., 2014), including much of the U.S. Corn belt which accounts for approximately 30% of the global maize production. Annual precipitation is also projected to increase, with greater change in the eastern range of the U.S. Corn Belt than the western range (IPCC, 2014). The majority of the increase is expected to occur during winter, while June, July, and August precipitation may actually decline (Sinclair, 2010; Knutti and Sedláček, 2013).

High temperatures, low soil moisture, and the combination of high temperature with low soil moisture can impact maize physiology and, ultimately, yield (Westgate and Hatfield, 2011; Prasad et al., 2008; Mittler, 2006). The specific physiological responses to temperature, moisture, or combined temperature/moisture stress, depend on the growth development phase (GDP) of the crop at the time of onset of stress (Barker et al., 2005). However, the relative impacts of temperature and low soil moisture on yield response can be difficult to determine using statistical modeling because of local collinearity between the two climate stressors. Soil moisture stress results in stomatal closure, decreased latent heat flux, and increased sensible heat transfer from vegetated surfaces to the atmosphere that can lead to higher local air temperatures. High temperature anomalies are therefore often the result of, and highly collinear with, periods of low soil moisture that follow negative precipitation anomalies (Trenberth and Shea, 2005). In addition, decreased latent heat loss by the crop canopy during soil moisture stress drives canopy temperatures above ambient air temperatures, particularly under high radiation loads (DeJonge et al., 2015). Moisture-stressed canopies can reach temperatures several

Abbreviations: GDP, growth development phase; MINK, Missouri/Iowa/Nebraska/Kansas; NCGA, National Corn Growers Association; CultGDD, cultivar maturity class; CLIM, linear mixed effects model with climate variables added as fixed effects; MGT, linear mixed effects model with management variables added as fixed effects; MJ, mega joules

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degrees higher than ambient air temperature (Siebert et al., 2014), so that heat stress thresholds established with air temperature may vary depending on soil moisture stress. Since higher air temperatures linked to greenhouse gas emissions may or may not be regionally or locally associated with reduced soil moisture conditions, statistical models relating current yield losses to high temperature anomalies in the presence of soil moisture stress may not provide robust predictions of future yield responses to increased temperature expected with climate change.

Crop management (e.g., crop rotation, tillage practices, planting date and planting rate, timing and quantity of fertilizer inputs, weed management, and pest management) directly impacts yield. Growers regularly modify management practices to make *a priori* adjustments to achievable yield based on perceived underlying local (including climatic) limitations on yield potential of a site or region. For example, cultivar maturity class and planting date are adjusted to account for expected length of the growing season, and planting rate is reduced in regions with low average growing season precipitation like the western U.S. Corn Belt (Lindsey and Thomison, 2016). These management variables, therefore, can follow similar spatial gradients as climate variables (USDA-NASS, 2007). Failure to adjust for non-climate factors like crop management that impact spatially distributed crop yields can lead to systemic bias in estimation of climate impacts on cropping systems in observational statistical studies that aggregate yield data across different locations (Challinor et al., 2015).

The above discussion indicates that climate impacts on maize yields will depend on interactions among the climate variables, as well as crop growth stage and crop management. Therefore, analyses of observational yield data at broad spatial scales to identify crop response to climate variability will require information on multiple collinear climate variables and their interactions that can propagate stress, data on the crop GDP at the time of stress, and the temperature, moisture (soil and/or precipitation) conditions, and management practices that preceded the stress event (Harrison et al., 2014). It will also require methods of statistical analysis that will not ascribe all of the variability in crop response to a single climatic variable in a situation with high levels of collinearity. This is especially relevant to studies of the impacts of projected climate change on crop yields, since the current correlation structure among climate variables (particularly precipitation and temperature) in a given region is not expected to remain the same under climate change (Seager et al., 2014).

Many common statistical routines applied to environmental data, including ordinary least squares (OLS) regression, are sensitive to collinearity (Dormann et al., 2013). Numerically, collinearity inflates standard errors of coefficient estimates and increases the likelihood of type 2 (false negative) errors in hypothesis testing. Practically, collinearity can lead to a situation where a variable or variables (precipitation) with a strong mechanistic control on the response variable (yield) may have an insignificant p-value, while a collinear predictor variable (temperature) with a smaller or no mechanistic control may appear significant.

Previously we showed that 2005–2012 growing season temperatures had minimal impact on irrigated maize yields in the western U.S. Corn Belt (Carter et al., 2016). Our analyses suggested that thermo-acclimation, adjustments to management practices and improved maize genetics could potentially offset expected negative impacts of higher temperatures, and that previously identified statistical relationships between high temperatures and yields in observational analyses may have been due in part to correlation between high temperature and low precipitation (Carter et al., 2016). Although studies conducted in controlled environments have reported evidence of physiological heat stress in maize (e.g., Hatfield, 2016), it remains unclear whether these physiological temperature stress thresholds are commonly exceeded under the current climatology of the U.S. Corn Belt when there is little or no underlying moisture stress. In this paper, we examine the impact of co-variable climate parameters (air temperature, precipitation, and radiation) and management parameters (planting rate, planting date, and cultivar maturity class) on rainfed maize yields in Missouri, Iowa, Nebraska and Kansas (MINK) using penalized (elastic net) regression (Zou and Hastie, 2005). This analysis is conducted on a novel dataset of rainfed yield entries from the National Corn Growers' Association (NCGA) Yield Contest—a dataset that includes detailed information on management. Using a series of nested linear mixed effects models, we evaluate whether maize yield response to high temperature is influenced by the timing of the stress event and precipitation concurrent with the stress event. We also evaluate whether failure to parameterize crop management factors, which spatially co-vary with climate in the MINK region (Supplementary materials (SM) Text S1, Fig. S1) and exert mechanistic control on regional yields, can lead to systematic bias in interpretation of climate impacts on inter-annual yield anomalies. To our knowledge, this is the first attempt to leverage detailed information on crop management practices to inform a regional statistical analysis of climate impacts on maize yield.

2. Methods

2.1. Maize yield, management, and climate data

Rainfed maize yield data for the MINK region from 2005–2012 were obtained from the NCGA National Yield Contest (http://www.ncga.com/for-farmers/national-corn-yield-contest). Farm-level yield contest data included county location, farm ID, maize yield, and a variety of management variables, including planting date, planting rate, previous crop, tillage practice, and cultivar name (SM Text S2, Fig. S2). A variety of climate variables were also considered, and were separated based on GDP – Early-growth (EG), Reproductive period (Sen), and Grain-fill (G). Table 1 summarizes the climate variables used in our analyses. Detailed information on the climate data and methods for defining GDP based on growing degree days (GDDs) can be found in SM Text S3 and Fig. S3, as well as in Carter et al. (2016). Detailed information on the calculation of antecedent available precipitation can be found in SM Text S4.

2.2. Model development

Six nested, linear mixed effects models were constructed to explore and isolate the impacts of different management and climate variables, and interactions among climate variables, on yield (Fig. 1). The simplest model (the NULL model) includes no covariates, but rather assigns random effects to each location and each year in the dataset. Thus, the NULL model accounts for site-specific differences in yield that are the same across each year in the 2005–2012 period ('Location' effect), and regional shifts in yield that are experienced at all sites in each year ('Year' effect). These random effects can be used to partition unexplained variance in the yield dataset (i.e., variance not explained by a covariate) into location-based and year-based variance components (discussed in Section 2.4). These random effects were also included in all other models. The first of these is a management-only model (MGT), which includes a detailed parameterization of several crop management variables: planting rate (PR), planting date (PD), cultivar maturity class (CultGDD), tillage (till), and previous crop (PC). The second model (CLIM) includes multiple climate variables by GDP. The third model (MGT + CLIM) combines the MGT and CLIM models to see how estimated climate coefficients in the CLIM model change when management covariates are included. Two other variants of the MGT + CLIM are also considered. These are the MGT + CLIM* model which includes interaction terms between climate variables to determine how these interactions change the interpretation of climate effects on yield, and the MGT + CLIM** model which includes yield response to interactions