



# Recent changes in county-level corn yield variability in the United States from observations and crop models



Guoyong Leng

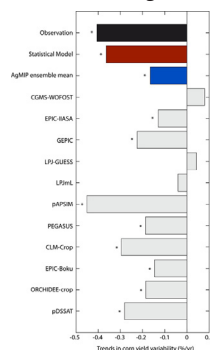
Joint Global Change Research Institute, Pacific Northwest National Laboratory, College Park, MD 20740, USA

## HIGHLIGHTS

- US corn yield variability has changed significantly with distinct spatial pattern.
- Corn yield variability increased in roughly one third of growing counties.
- Current state-of-art crop models partly reproduced the observed change pattern.
- Climate variability contributes the most to the changes in statistical model.
- Irrigation influences the magnitude and even the change sign of yield variability.

## GRAPHICAL ABSTRACT

Change trends of corn yield variability (%/yr) based on observations and simulations by statistical model and 11 AgMIP gridded crop models for the whole country as a whole. 15-year time window during 1980–2010 is used to calculate the interannual variability, based on which the linear trend is fitted and normalized by the mean yields. \*indicates the significant trend at the 95% level.



## ARTICLE INFO

### Article history:

Received 24 May 2017

Received in revised form 1 July 2017

Accepted 2 July 2017

Available online xxxx

Editor: Jay Gan

### Keywords:

Crop yields

Variability

Stability

Climate change

Crop models

Statistical models

## ABSTRACT

The United States is responsible for 35% and 60% of global corn supply and exports. Enhanced supply stability through a reduction in the year-to-year variability of US corn yield would greatly benefit global food security. Important in this regard is to understand how corn yield variability has evolved geographically in the history and how it relates to climatic and non-climatic factors. Results showed that year-to-year variation of US corn yield has decreased significantly during 1980–2010, mainly in Midwest Corn Belt, Nebraska and western arid regions. Despite the country-scale decreasing variability, corn yield variability exhibited an increasing trend in South Dakota, Texas and Southeast growing regions, indicating the importance of considering spatial scales in estimating yield variability. The observed pattern is partly reproduced by process-based crop models, simulating larger areas experiencing increasing variability and underestimating the magnitude of decreasing variability. And 3 out of 11 models even produced a differing sign of change from observations. Hence, statistical model which produces closer agreement with observations is used to explore the contribution of climatic and non-climatic factors to the changes in yield variability. It is found that climate variability dominates the change trends of corn yield variability in the Midwest Corn Belt, while the ability of climate variability in controlling yield variability is low in southeastern and western arid regions. Irrigation has largely reduced the corn yield variability in regions (e.g. Nebraska) where separate estimates of irrigated and rain-fed corn yield exist, demonstrating the importance of non-climatic factors in governing the changes in corn yield variability. The results highlight the distinct spatial patterns of corn yield variability change as well as its influencing factors at the county scale. I also caution the use of process-based crop models, which have substantially underestimated the change trend of corn yield variability, in projecting its future changes.

© 2017 Elsevier B.V. All rights reserved.

E-mail address: [Guoyong.Leng@pnnl.gov](mailto:Guoyong.Leng@pnnl.gov).

## 1. Introduction

With increases in population, global food demand is expected to roughly double by 2050s (Godfray et al., 2010; Tilman et al., 2011). The United States is responsible for ~35% and ~60% of global corn supply and exports (USDA–NASS, 2016; USDA–ERS, 2017). Enhanced supply stability through a reduction in the year-to-year variability of US corn yield would greatly benefit the global food system. In fact, recent food crises highlighted the need for better understanding of the year-to-year variability of agricultural productions (Schmidhuber and Tubiello, 2007). Therefore, analyses of historical variations of U.S. corn yield can provide much needed insight into future food security and adaptation measures. Previous global and regional scale studies showed that crop yield variability has changed in the past (Hazell, 1984; Naylor et al., 1997; Calderini and Slafer, 1998; Reilly et al., 2003; Kucharik and Ramankutty, 2005; Osborne and Wheeler, 2013; Iizumi and Ramankutty, 2016). However, finer-scale analysis on the spatial pattern of changes in crop yield variability across the whole country is rare, despite the fact that the level of temporal variability depend largely on the spatial scale at which it is considered.

Variation in crop yield from one year to the next is caused by, among others, fluctuations in weather, pest diseases, agricultural management, technology and etc. (Asseng et al., 2013; Hawkins et al., 2013; Challinor et al., 2014; Zhao et al., 2016; Leng and Huang 2017; Leng, 2017; Schauburger et al., 2017). Predicting the response of crops to environmental changes has to rely on models that translate changes in climatic and non-climatic conditions to changes in agricultural outcomes. There are generally two common approaches to assess these impacts: process-based simulation models representing key dynamic processes affecting crop yields (Deryng et al., 2011; Rosenzweig et al., 2013; Leng et al., 2016b) and statistical models estimating functional relationships between historical observations of weather and yields (Lobell and Burke, 2010; Leng et al., 2016a). Based on the two approaches, an increasing number of studies have examined the impact of climate variability on crop yield (Ray et al., 2002; Rosenzweig et al., 2002; Lobell and Asner, 2003; Schlenker and Roberts, 2009; You et al., 2009; Sakurai et al., 2014; Leng et al., 2016a; Lesk et al., 2016; Leng and Huang 2017; Leng, 2017). Whilst these studies acknowledged the importance of climate variability in influencing yield variability, the contribution of climate variability to the temporal evolution of crop yield variability is unclear at fine scales.

Recently, the process-based modeling community has completed several model intercomparison studies within the framework of the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013). However, to what extent, these process-based simulation models capture the observed changes in crop yield variability is unclear. Indeed, knowledge of how current state-of-art crop models perform in simulating historical yield variability changes has great implication for future projection of corn yield variability using process-based crop models. In this study, I investigate the temporal evolution of year-to-year variability of corn yield at the county scale across US. Specifically, I will address the following three scientific questions: 1) How corn yield variability have changed during the past three decades? and 2) How process-based and statistical crop models perform in simulating the changes in corn yield variability? Such a validation is important for justifying the selection of process-based or statistical model for addressing the third question: How much climatic and non-climatic factors have contributed to the changes in corn yield variability for each growing county?

## 2. Materials and methods

County-level corn yield for 1981–2010 are obtained from the National Agriculture Statistics Survey's Quick Stats database by the US Department of Agriculture (USDA) (<http://www.nass.usda.gov/QuickStats>). Separate estimates of irrigated and rainfed corn yield are also

collected from the USDA database, which only exist for a limited number of counties mainly located in central Great Plains. The interannual variability of corn yield is estimated by the standard deviation of annual corn yield anomalies with linear trend removed. 15 year time window is used during 1980–2010 and 17 samples of variability are derived, based on which the change trend of yield variability is calculated. The statistical significance of change trend is estimated according to the two-tailed Student's *t*-test. The 15-year time window is selected given the data length and sample size requirement for robust statistics. Analysis is repeated using smaller and larger time windows to examine the sensitivity of the results to the choice of time window.

The climate data for 1981–2010 is obtained from the AgMERRA climate data set, which is developed specifically for agricultural impact assessments (Ruane et al., 2015). To quantify climate variability impacts on corn yield variability must rely on models that translate changes in climate to changes in agricultural outcomes. There are generally two common approaches to assess these impacts, i.e. process-based simulation models and statistical models (Lobell and Asseng, 2017). As for the statistical approach, I fit the multiply regression model with corn yield variability as the dependent variable and growing season temperature and precipitation variability as the predictors. Growing season temperature and precipitation is aggregated into county scale with weights given by the gridded crop area map from MIRCA2000 (Portmann et al., 2010). I also use simulated corn yields by eleven gridded crop models (Table 1) from the Agricultural Modelling Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013) and the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) (Warszawski et al., 2014). These crop models were driven by the same climate data (i.e. AgMERRA climate) as used in the statistical model. In this study, no certain criterion is adopted for selecting process-based crop models for analysis. Instead, all available simulations from those models contributing to the AgMIP and ISI-MIP projects are used.

Based on validation results, several scenarios of climate conditions are designed as inputs into statistical model in order to investigate the effects of changes in climate variability on corn yield variability changes following Lobell and Burke (2010). Specifically, four scenarios of historical time series of T and P are derived: (i) actual T and actual P variability time series for each county, (ii) actual T and detrended P variability time series, (iii) detrended T and actual P time series, and (iv) detrended T and detrended P time series. The derived time series are fed into the fitted statistical model and corn yield variability is predicted. Trend in the difference of predicted corn yield variability between (iv) and (i) is used to quantify the impact of climate variability, whereas (ii) and (iii) are used to determine the relative contribution of T and P to overall impacts, respectively. Climate variability is taken as the dominant factor in regulating yield variability changes when more than

**Table 1**  
Description of crop models used in this study.

Crop model	Model type	Key literature
CGMS-WOFOST	Spatially distributed site-based process model (based on WOFOST)	(de Wit and Van Diepen, 2008)
CLM-Crop	Global ecosystem model	(Drewniak et al., 2013)
GEPIK	Site-based process model (based on EPIC)	(Williams et al., 1983; Liu et al., 2007)
LPJ-GUESS	Global ecosystem model	(Lindeskog et al., 2013)
LPJmL	Global ecosystem model	(Waha et al., 2012)
pAPSIM	Site-based process model	(Keating et al., 2003)
PEGASUS	Global ecosystem model	(Deryng et al., 2016)
EPIC-IIASA	Site-based process model (based on EPIC)	(Balković et al., 2014)
EPIC-Boku	Site-based process model (based on EPIC)	(Kiniry et al., 1995)
ORCHIDEE-crop	Global ecosystem model	(Wu et al., 2016)
pDSSAT	Site-based process model	(Jones et al., 2003)

Download English Version:

<https://daneshyari.com/en/article/5750025>

Download Persian Version:

<https://daneshyari.com/article/5750025>

[Daneshyari.com](https://daneshyari.com)