Spatial Visualization of Historical Drought Impact on Agriculture in North and South Carolina

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Introduction

Drought events have had severe impacts on agriculture in the Carolinas. Attempts to quantify and compare these impacts across space and time have been challenging because of the nonlinear and non-stationary nature of crop yield time series. Crop yield and production are controlled by many factors including scientific and technological advances (e.g., improvements in plant genetics, fertilizer, pesticides, and irrigation facilities), as well as weather and climate. This study evaluates detrending methods to distinguish technology advances from weather and climate factors and allow spatial visualization of drought impact on agriculture. We use long-term state- and county-level corn/soybean yield data in North and South Carolina to illustrate our results.

Non-linear and Non-stationary Nature of Crop Yield Time Series

Increasing yield results because of technological advances while high-frequency fluctuations reflect weather and climate factors (Fig. 1). Collectively, they make long-term crop yield data nonlinear and non-stationary (varying mean and standard deviation). This hampers comparison and spatial visualization of drought impacts on agriculture. For example, comparing impacts of the past droughts with the more recent 2011 drought is difficult because of the technology trend. Modeling and spatial visualization of drought impacts on agriculture requires appropriate distinctions between the high frequency fluctuations caused by the climate variability and the long-term trend caused by technological factors.

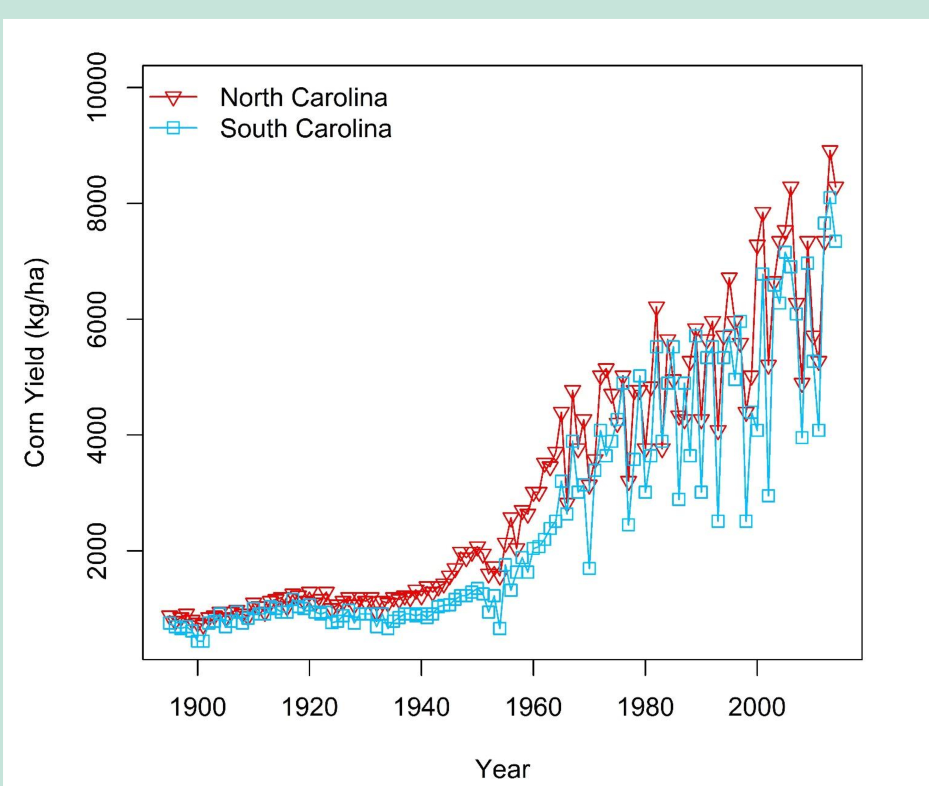


Fig. 1. Corn yield time series from 1895 to 2014 in North Carolina and South Carolina

Data

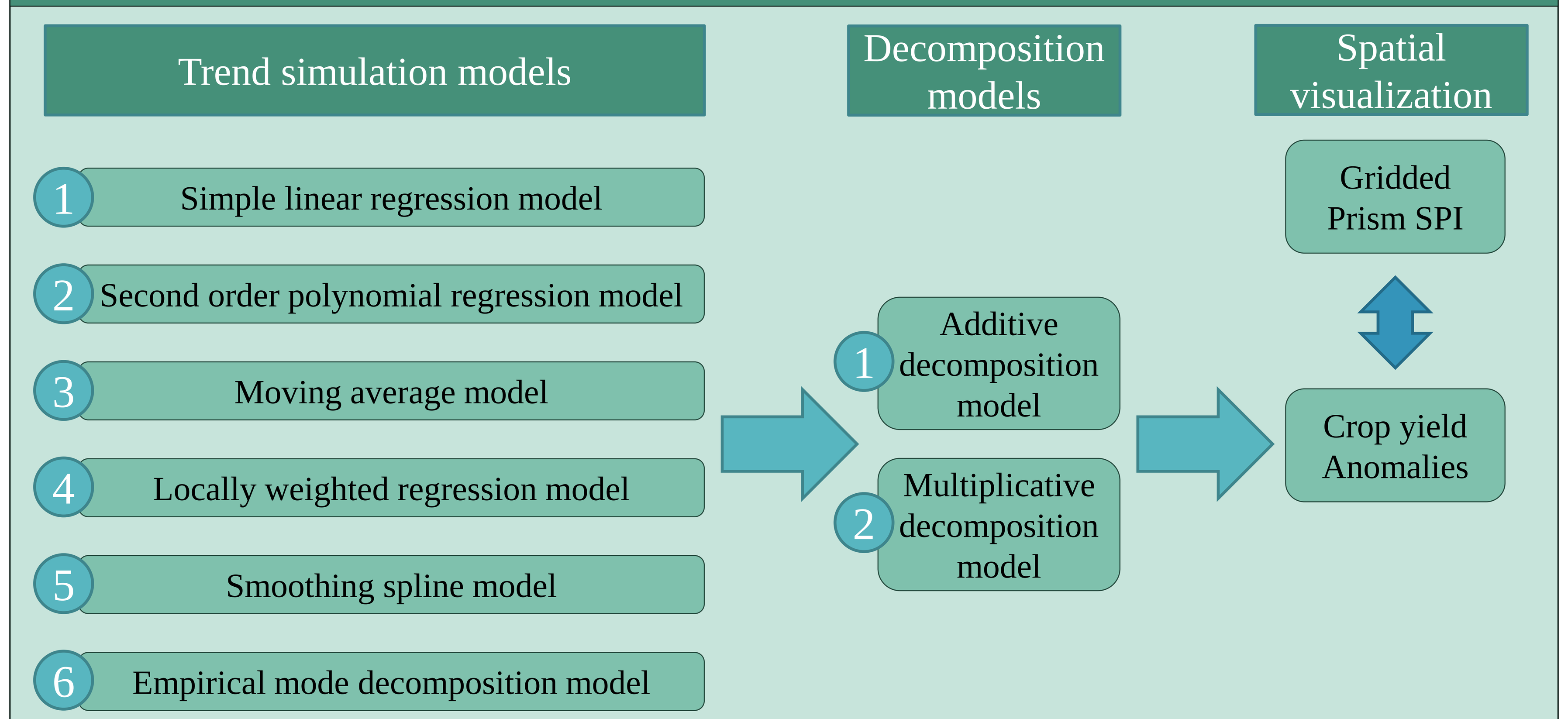
❑ Agriculture data

Long-term corn yield and soybean yield were obtained from USDA's National Agricultural Statistics Service.

❑ Prism data

4-km gridded PRISM (Parameter-elevation Relationships on Independent Slopes Model) precipitation data set are downloaded from PRISM Climate Group (http://www.prism.oregonstate.edu/). For each pixel, standardized precipitation index (SPI) was calculated following the method of McKee et al. (1993) by fitting a two-parameter gamma distribution.

Methodology



Trend Simulation Models Comparison

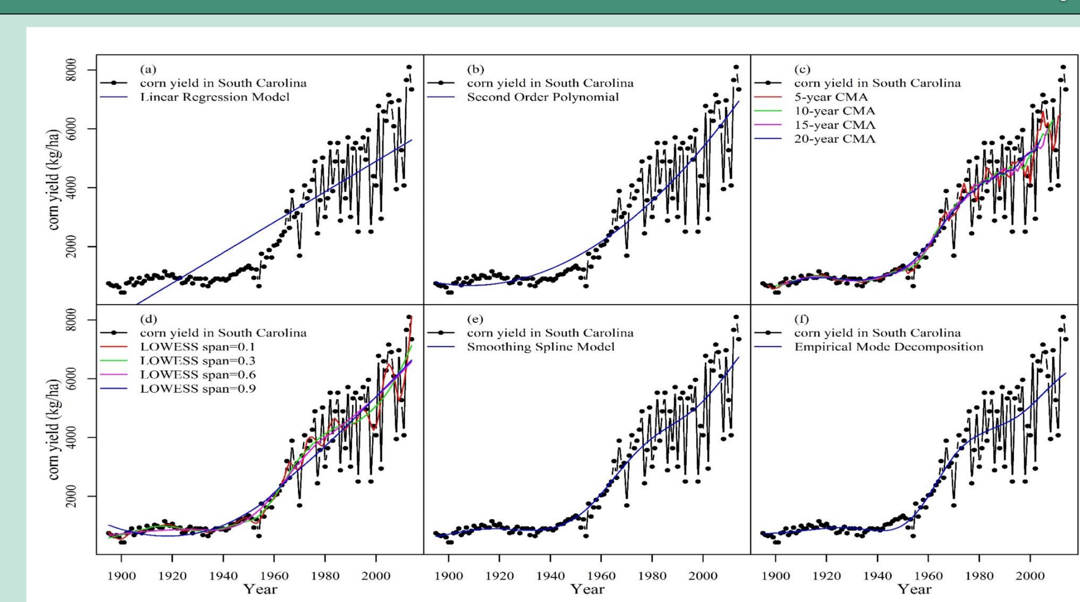


Fig. 2. Trend simulation models comparison (Data: corn yield from 1895 to 2014 in South Carolina)

- The simple linear regression and second order polynomial regression models cannot capture the long-term non-linear increasing trend and had the poorest fit.
- The other four methods fit state-level corn yield very well and exhibited similar accuracy, but have respective advantages and disadvantages.

i. The centered moving average model is limited by its boundary problems.
ii. Empirical mode decomposition model (EMD) requires visual inspection and manual application and employing it to detrend crops for hundreds of counties is time consuming and impractical.
iii. Smoothing spline models do not perform well with shorter data records (e.g., fewer than 60 years), converging to traditional interpolation spline.
iv. The locally weighted regression model is data self-adaptive, which can automatically follow the underlying pattern of the nonlinear crop yield time series.

Decomposition Models Comparison

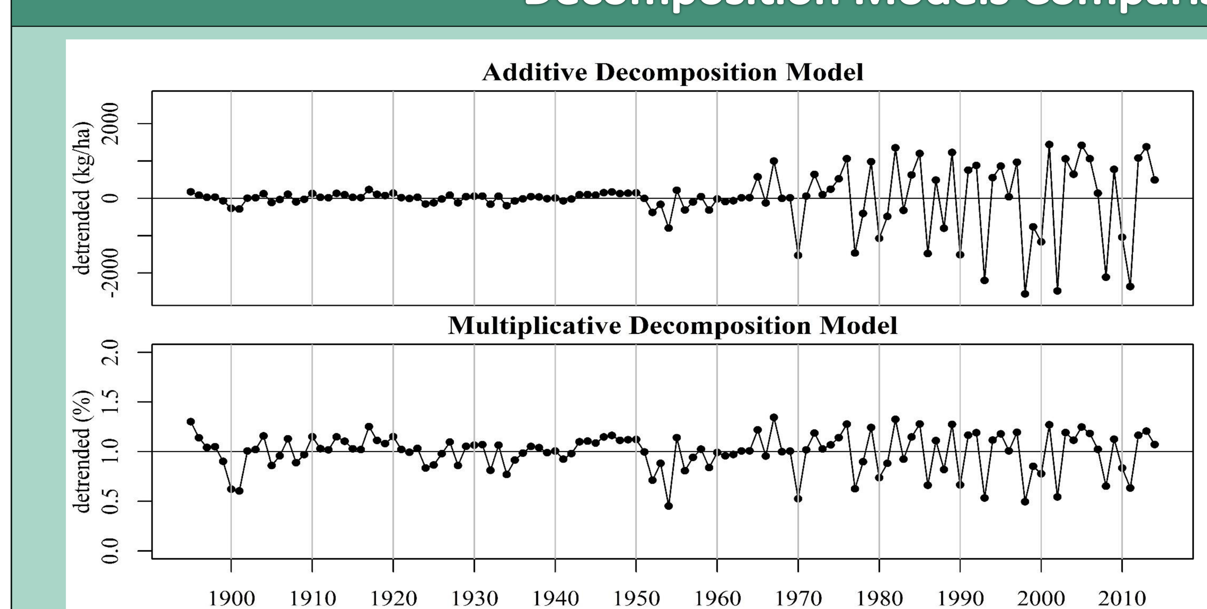


Fig. 3. Comparison of an additive decomposition model and a multiplicative decomposition model (Data: corn yield from 1895 to 2014 in South Carolina; trend simulation method: locally weighted regression model)

- After applying an additive decomposition model to remove the trend from the time series, the variance of detrended corn yield in South Carolina increases with time.
- A multiplicative decomposition model is more appropriate because the variance of the detrended data is adjusted to the magnitude of crop yield, becoming more stationary through time. Detrended crop yield minus one represents the percentage lower or higher than normal yield conditions, termed "crop yield anomaly".

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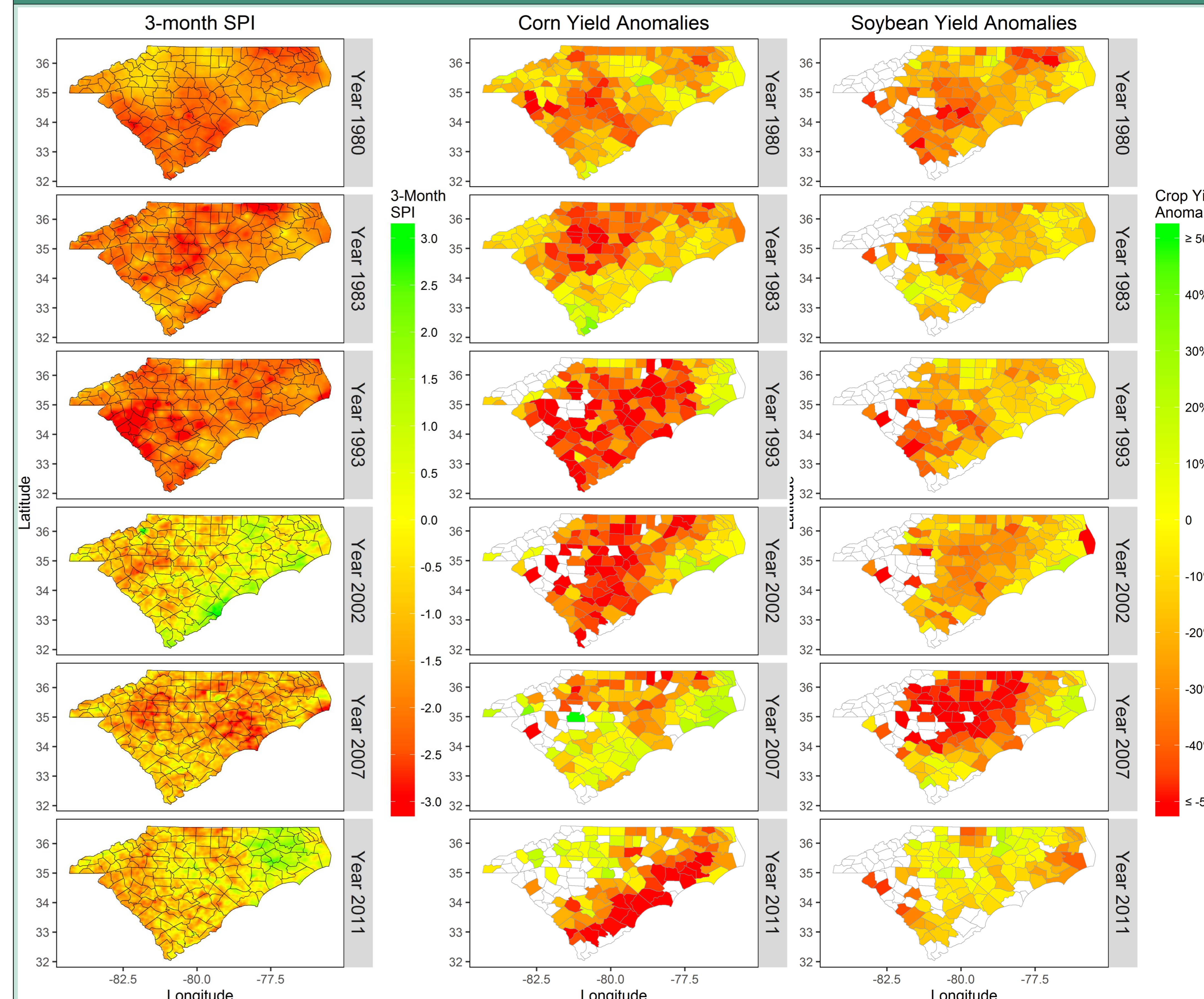

Fig. 4. Spatial visualization of county-level corn/soybean yield anomalies accompanied with August 3-month SPI in Carolinas for six historical drought years: 1980, 1983, 1993, 2002, 2007, and 2012. (Data: gridded August 3-month SPI calculated from PRISM; county-level crop yield anomalies detrended by combination of locally weighted regression models and multiplicative decomposition models)

- The locally weighted regression model, coupled with multiplicative decomposition model, is the appropriate data self-adaptive method to detrend the crop yield.
- Through correlation analysis between SPI of different time scales and corn/soybean yield anomalies, we found that 3-month SPI in August shows the highest correlation with detrended corn/soybean yield.
- We used this detrending approach to detrend yield and compare corn/soybean yield responses to drought across six major drought years. The gridded 3-month SPI in August calculated from the 4-km gridded PRISM data are used as a reference of drought severity.
- Comparisons between August 3-month SPI and corn/soybean yield anomalies for these six drought events show a strong correspondence between dryness and lower than normal corn/soybean yield.

Conclusion

- This study identifies the most appropriate data self-adaptive detrending method to standardize and detrend the crop yield by comparing multiple detrending methods.
- The detrending method allows comparing drought impacts on agriculture across both space and time and long-term spatial visualization of drought impact on agriculture.

Acknowledgements

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