Tropical Cyclone Impacts on Crop Condition Ratings and Yield in the Coastal Southern United States

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ABSTRACT

Weather causes both positive and negative impacts to agriculture making it the most uncontrollable factor affecting crop production. Agriculture in the southern U.S. comprises over 40% of the annual commodity export from the U.S., and this region also experiences a relatively large frequency of tropical cyclones. Few previous studies have investigated the effects tropical cyclones have on agriculture; thus, this study quantified the role tropical cyclones have on crop quality and yield in the Coastal Southern U.S. region using United States Department of Agriculture National Agricultural Statistics Service crop condition data (May–October; 1986–2021). The greatest changes in condition ratings were observed in fields that were favorable for normal and above normal yield potential, which were downgraded to a less than normal condition more favorable for some extent of loss to yield. For crops considered in excellent or good condition, decreases in coverage were up to 5% which resulted in an increase in fair, poor,

Abbreviations: CCI, Crop Condition Index; NASS, National Agricultural Statistics Service; NOAA, National Oceanic and Atmospheric Administration; TC, tropical cyclone; USDA, United States Department of Agriculture

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or very poor conditions (up to 3% on average). When aggregating all crops in this study (corn, cotton, peanuts, rice, sorghum, soybean), the latter portion of the growing season was the most detrimental to conditions after tropical cyclone impact, even under drought conditions. The strongest correlation found was between crop condition declines and tropical cyclone intensity, as major hurricanes were more likely to cause crop loss than any other variable. Consequently, yield prospects decline after a tropical cyclone based on declines in coverage of excellent and good conditions (yield declines up to 6% on average); though, crop conditions tend to recover resulting in yield to also recover marginally by the end of the season (declines up to 3%). Overall, these results provide essential risk management information for producers and could be used to better inform resilience and sustainability decisions related to tropical cyclone impacts.

Keywords: crop conditions, crop yield, tropical cyclones, weather, regional climate

1. INTRODUCTION

Agriculture is one of the most sensitive economic sectors to weather and climate due to its direct and uncontrollable impact on crop production (Andresen et al., 2001; Knox et al., 2014). In particular, the South U.S. region has an especially important agricultural sector producing many high valued crops such as citrus, vegetables, and several field crops including soybean, hay, corn, wheat, cotton, peanuts, sorghum, and more (Hatch et al., 1999). Agriculture in the South is a significant source of commerce, with over $55 billion USD in commodity production annually accounting for nearly 17% of total U.S. production (Asseng, 2013). In order to maximize commodity production, continuous monitoring of crops throughout the growing season provides valuable insight into crop quality, health, and productivity that stakeholders use to make real-time decisions (Khaki et al., 2021).

Unique to the Coastal South when compared to other agricultural belts in the U.S.—and something to be considered by stakeholders—is increased exposure to tropical cyclones (TCs). TCs are among the most destructive natural hazards on the planet (Kunze, 2021) and can cause irreparable damage to agriculture in the form of destruction to vegetation, damage to irrigation facilities, and long-term loss of soil fertility (Xu et al., 2005). Perils associated with a single TC event, such as the flooding, can destroy an entire season's yield (Knox et al., 2014). Recently, the USDA starting issuing hurricane-specific crop insurance and has expanded to cover all tropical cyclones to provide as a financial safety net against crop losses (USDA, 2020). In terms of damage, Tropical Storm Fay in August 2008 resulted in over $250M USD in losses to agriculture in northern Florida and southern Georgia, in part because 70% of the expected production value was lost for vegetable crops (Flanders et al., 2008). On the extreme end, Hurricane Katrina in August 2005 caused sugar cane, corn, soybean, and cotton production losses totaling approximately $1B USD (Schnepf and Chite, 2005). Other literature has investigated the detrimental effects TCs have had on agricultural sectors across the globe, including China (Xu et al., 2005), Bangladesh (Hossain et al., 2008), Central America (Boucher et al., 2001), and the Caribbean Islands (Bertinelli et al., 2016), as well as TC impact based on land use and topographic features (Philpott et al., 2008) and the effects on agriculture from an economic standpoint under a changing climate (Chen and McCarl, 2009). In terms of a changing climate, increasing TC frequency and intensity has been debated considerably within the context of global climate change and natural variability (Emanuel, 2005; Webster et al., 2005; Landsea et al., 2006; Shepherd and Knutson, 2007, Kossin et al., 2010; Knutson et al., 2010; Seneviratne et al., 2012; Villarini et al., 2012; Weinkle et al., 2012; Knutson et al., 2013), which emphasizes the importance of investigating tropical cyclone impacts in the Coastal Southern U.S. Despite this debate, TC impacts from heavy rain and damaging winds are costly and have a varying response depending on the agroecosystem and its vulnerability (Perotto-Baldiviezo et al., 2004; Philpott et al., 2008). Therefore, if tropical cyclone frequency and/or intensity continues to increase in the future (Emanuel, 2007; Bender et al. 2010; Bell et al., 2011; Tron and Snyder, 2012; Landsea and Franklin, 2013), the implications to agriculture in the Coastal Southern U.S. will amplify.

Heavy rain from TCs can lead to inundated fields resulting in disease and root rotting as daily rainfall amounts from TCs average between 150–350mm across all aggregated cyclone strength classifications (Cerveny and Newman, 2000). Heavy rainfall effects to agricultural fields also holds true for non-TC excess precipitation events (Knox et al., 2014; Bundy et al., 2022). In general, flooding associated with landfalling TCs has claimed a large economic and societal toll with several billion dollars in damage annually to the U.S. (e.g., Rappaport, 2000; Pielke et al., 2008; Changnon, 2008; Mendelsohn et al., 2012; Peduzzi et al., 2012). Despite these repercussions, there is limited published literature about the inland flooding from TCs when compared to improving the understanding of damage caused by storm surge and wind (e.g., Elsberry, 2002; U.S. Department of Commerce, 2011; Zandbergen, 2009; Villarini et al., 2014). This is especially true when it comes to TC-induced rainfall impacts on crop quality. Flooded land also impacts soil structure (Kopyra and Gwo d, 2004; Pengthamkeerati et al., 2006; Haddad et al., 2013; Kraur et al., 2019) and if there is little soil integrity or strength, then crops are more susceptible to being damaged by wind (Cleugh et al., 1998). In general, excessive winds from TCs pose a threat for greensnap or root lodging, resulting in downed fields, a reduction in crop quality, and ultimately a loss in production (Cleugh et al., 1998; Lindsey et al., 2021). Even with these TC perils, previous literature (e.g., Rodgers et al., 2001; Knight and Davis, 2007) has noted that the contribution of TC-induced rainfall has been overlooked, as rainfall from TCs can be essential for the success of the agricultural enterprise in the Coastal South U.S. region. TC-induced rainfall comprises between 5–15% of the growing season rainfall total for much of the region (Knight and Davis, 2007). In addition, if all TC-induced rainfall was removed in a given season, soil moisture deficits in the Southern U.S. would increase by approximately 20–30%, on average (Knight and Davis, 2007). The timing of TC rainfall is likely an important contributor to whether it would benefit a crop, and there is a risk versus reward factor when it comes to beneficial TC rainfall versus potential wind damage. Neither of these are well understood and would benefit from a quantitative analysis.

A widely used methodology to perform continuous monitoring of crops is through the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Crop Progress report. The report is crucial for speculators in agriculture future markets (Bain and Fortenbery, 2013; Lehecka, 2014). Crop Progress reports released by the USDA

NASS have been argued to capture the complexities of assessing the "status" of a crop better than any model or remote sensing retrieval (Begueria and Maneta, 2020) and have had statistically significant correlations with weather/climate variables and yield (Bundy and Gensini, 2022). Therefore, with existing discrepancies in previous literature regarding whether TCs are overall beneficial, detrimental, or perhaps both to agriculture, this study aimed to quantify historical TC impacts on crop quality and yield in the Coastal South U.S. region. In particular, the goals of this study were to 1) quantify the impacts TCs have had on conditions across multiple field crops, 2) quantify the intermonthly impacts TCs may have had on crop conditions, 3) characterize how TC intensity and precursor soil moisture impacted crop conditions, and 4) quantify historical yield changes based on the crop conditions. A comprehensive overview of crop quality and yield impacts by TCs using USDA NASS data has not been performed to date. The novel results herein can be used by farmers, insurers, agronomists, and other stakeholders to aid in the decision-making process regarding management and resilience when it comes to TC impacts on regional agriculture.

2. MATERIAL AND METHODS

2.1. Crop condition data

Weekly USDA NASS Crop Progress crop condition data were obtained from May–October, 1986–2021, for eight states we define as the Coastal South U.S.: Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina, and North Carolina (USDA, 2022). General crop condition data includes corn, cotton, peanuts, rice, sorghum, and soybean as they are the most widespread in terms of yield (Fig. 1), production (Appendix A), and acreage

(Appendix B) within this region. Condition data varied temporally by crop and by state—not all states had the same number of years of data for each crop examined.

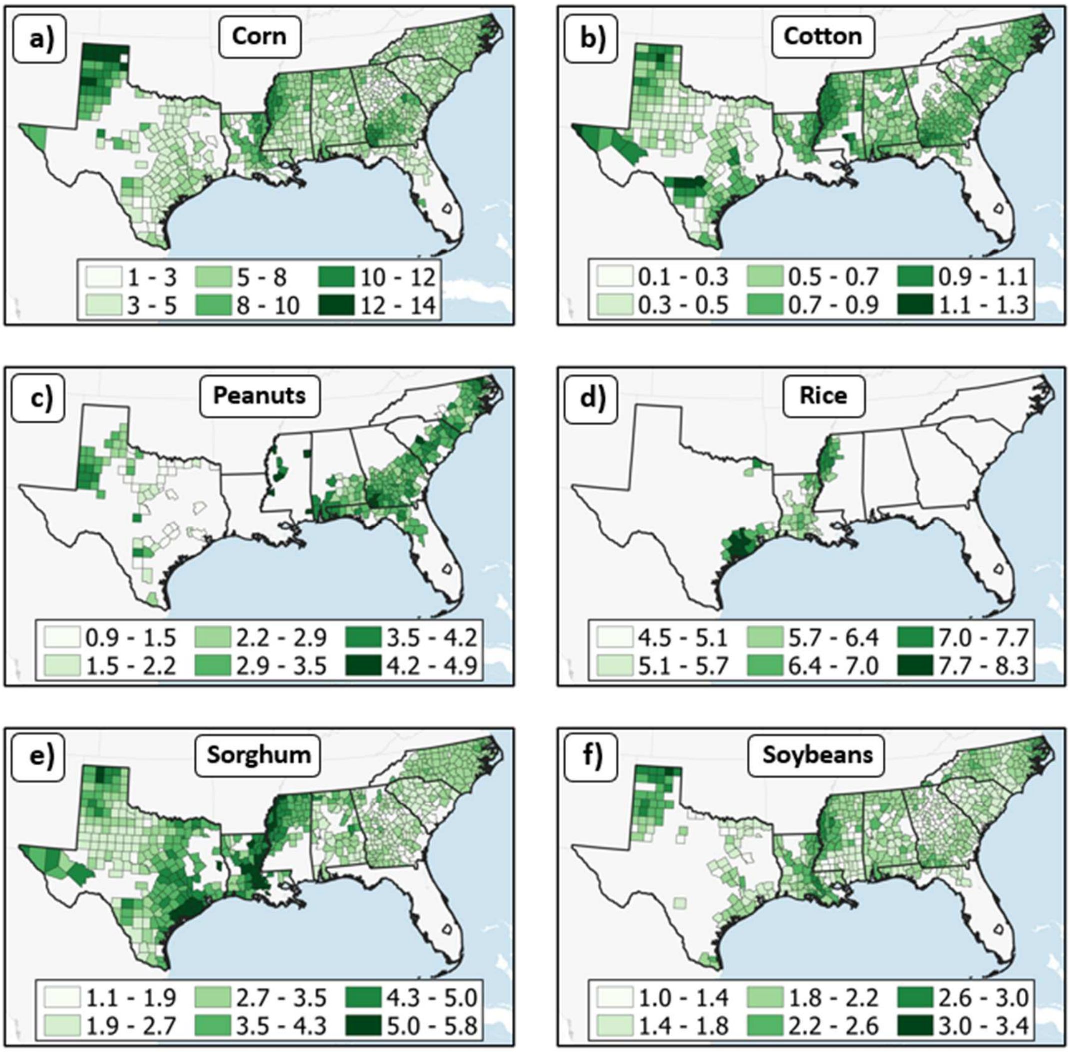

Fig. 1. Average annual yield (kg ha^{-1} in thousands) at county-level for each crop examined in the Coastal Southern U.S. region (1986–2021). Locations within the study area without a county outline did not have any production for the respective crop. (*Color not needed for print)*

For example, corn condition data for Texas are available from 1986–present, though for Louisiana, Alabama, and Georgia, corn condition data only date back to 2007. Cotton, soybean, sorghum, and rice data were available for all states from 1986–present, whereas peanut data were only available dating back to 1996. It is important to emphasize that a consistent sample size by state and/or crop was not necessarily important for this study, as attaining the greatest number of TC impact cases possible for examination was prioritized.

Weekly data collected by the USDA within each county are summarized and weighted by acreage to inform state-level data. Thus, public data via the USDA NASS are available only at state-level aggregation. Crop condition data are not released at the county level in part to protect the confidentiality of growers whose operations may comprise much of the production in a given county (USDA, 2021). These data are gathered via a weekly survey by reporters consisting of largely extension agents and Farm Service Agency staff (USDA, 2016). Approximately 3,600 respondents are asked to report for the entire week ending on Sunday, regardless if they submit their report on Friday, Saturday, or Sunday (USDA, 2021). For reports submitted prior to the Sunday reference date, a degree of uncertainty is introduced by projections for weekend changes in progress and condition. By the end of the 2020 season, over 95% of the data were being submitted through an online portal. As a result, most reports were submitted on Monday morning, significantly reducing projection uncertainty (USDA, 2021). For the general crop conditions portion of the report, reporters are asked to estimate the percent of their crop in excellent, good, fair, poor, and very poor condition. General crop condition categories defined by the USDA are as follows:

- *Excellent* - Yield prospects are above normal. Crops are experiencing little or no stress. Disease, insect damage, and weed pressures are insignificant.
- *Good* - Yield prospects are normal. Moisture levels are adequate and disease, insect damage, and weed pressures are minor.

- *Fair* - Less than normal crop condition. Yield loss is a possibility, but the extent is unknown.
- *Poor* - Heavy degree of loss to yield potential which can be caused by excess soil moisture, drought, disease, etc.
- *Very Poor* - Extreme degree of loss to yield potential, complete or near crop failure.

The Crop Condition Index (CCI) was calculated for each report through the following equation (Bain and Fortenbery, 2013, 2017):

$$CCI = \%Excellent\ (1.0) + \%Good\ (0.75) + \%Fair\ (0.50) + \%Poor\ (0.25) + \%Very\ Poor\ (0)$$

This weighted index provides a value summarizing the current state of weekly conditions from the five crop conditions. The index ranges from [0, 100], with an index value of 100 corresponding to 100% of the surveyed crop being reported in excellent condition (Bain and Fortenbery, 2013, 2016). The 0 weight on the very poor condition percentage is used to eliminate the effect abandoned acres has if used for a yield forecast (Fackler and Norwood, 1999; Jorgensen and Diersen, 2014). We note there are other ways one might use the crop condition information provided by the USDA. For example, the USDA use their own weighted index, ranging from [1, 5] that combines all conditions together (similar to the Bain and Fortenbery (2013) approach) where an index of 1 corresponds to 100% of the crop being in very poor condition while an index of 5 corresponds to 100% of the crop being in excellent condition (Rosales, 2021). Other approaches include adding the percent of crop rated excellent and percent rated good and use that index to model corn and soybean yields (Irwin and Good, 2017a, 2017b; Irwin and Hubbs, 2018). However, Bain and Fortenbery (2016) argue that only using the good and excellent rating information is a disadvantage since responses from changes in the bottom three categories (fair, poor, very poor) are not considered. Also, the Bain and Fortenbery (2016)

CCI has been proven to represent the overall crop condition and use as an explanatory variable in modeling crop yields and production (Fackler and Norwood, 1999; Jorgensen, 2014; Jorgensen and Diersen, 2014; Bundy and Gensini, 2022).

2.2. Crop yield data

Crop yield data were also obtained from the USDA NASS from 1986–2021 for each Coastal South state for each crop examined (USDA, 2022). A linear trend adjustment was computed for each state for each growing season to eliminate the long-term trends of yield within each state. The linear trend was calculated dating back to when the crop condition data were first available for each state and crop in order to keep the comparison between conditions and yield consistent. The trend was computed by calculating the least-squares regression slope between the yield and the year index. Least-squares regression was used across all crops and states since each trend was approximately linear. This slope value was used to then detrend the yield data for each state and crop. The equation (Equ 1) used to detrend the yield for each crop and state is as follows (Irwin and Good, 2017a; Bundy and Gensini, 2022):

$$\mathrm{Yield}_{\mathrm{adj}} = \mathrm{Yield}_{\mathrm{t}} + [\beta_1\ (x_i - x_n)] \qquad 1$$

where Yield_t is the observed yield for year t. β_1 is the rate of change in the data, x_i is the total number of years used, and x_n is the year index. Yield for crops was collected from the USDA NASS database as follows: cotton in $lb \cdot ac^{-1}$, corn in $bu \cdot ac^{-1}$, peanuts in $lb \cdot ac^{-1}$, rice in $lb \cdot ac^{-1}$, sorghum in $bu \cdot ac^{-1}$, and soybean in $bu \cdot ac^{-1}$. These units were converted to $kg \cdot ha^{-1}$ to keep yield units consistent across the analysis. While the use of the USDA NASS database has proven reliable in a peer-reviewed research setting (e.g., Bundy and Gensini, 2022), there are shortcomings of the database worth noting. First, between the use of the crop conditions and yield, the statistics may be impacted by the growth stage of the crop. Hence, more crop deterioration/yield loss may occur to crops that are further along in their growing cycles in more southern location than further north within a state. With this, the data at state-level aggregation is a limitation. Second, these statistics do not account for the practice of double-cropping which may impact the timing of the planting date, growth cycle, and in turn, the variability in crop conditions and yield. Finally, the comparison between crop conditions and yield in the USDA NASS database cannot account for irrigation. In other words, these data are not separated by rainfed and irrigated crops which may also impact variability in the results.

2.3. Tropical cyclone data

TC data were compiled from the National Oceanic and Atmospheric Administration (NOAA) Historical Hurricane Tracks database from May–October, 1986–2021 (NOAA, 2021). Tropical depressions (TD), tropical storms (TS), and Category 1 (H1), 2 (H2), 3 (H3), and 4 (H4) hurricanes were obtained for this analysis. No Category 5 hurricanes impacted crop area during the 1986–2021 study period. It is important to note that there were Category 5 hurricanes that made landfall during the study period, and there were some cases where hurricanes were upgraded to a Category 5 hurricane after the storm. These two examples include Hurricane Andrew and Michael as they were not initially considered Category 5 hurricanes at landfall (Landsea et al, 2004; NOAA, 2019). Nonetheless, these two storms were not Category 5 hurricanes once they went over cropland. The specific number of cases for each state, crop, and type of TC impacting each state were sorted (**Table 1**). TCs were classified based on their maximum intensity when affecting the respective crop area in any state in the study domain. The cyclone center of circulation (**Fig. 2**) needed to cross over at least one county with crop production (**Fig. 1**) to be counted as “impacting crop area” for this analysis.

Table 1. Report totals for each Coastal Southern U.S. state divided by crop type and tropical cyclone intensity (1986–2021).

	Totals by Crop Type							Totals by Tropical Cyclone Intensity						
State	Corn	Cotton	Peanuts	Rice	Sorghum	Soybean	Total	TD	TS	H1	H2	H3	H4	Total
Texas	25	25	3	16	24	4	97	4	14	6	2	2	1	29
Louisiana	1	9		15	9	16	50	6	4	5		1	1	17
Mississippi	3	15	3	3	3	15	42	10	5	1				16
Alabama	5	35	24			17	81	20	7	4	1	2	1	35
Florida		6	28				34	10	24	3	1	3	1	42
Georgia	11	30	21			16	78	15	16	1				32
South Carolina	5	20	11			12	48	11	9	3			1	24
North Carolina	30	23	22			29	104	9	13	4	3	2		31
Total	80	163	112	34	36	109	534	85	92	27	7	10	5	226

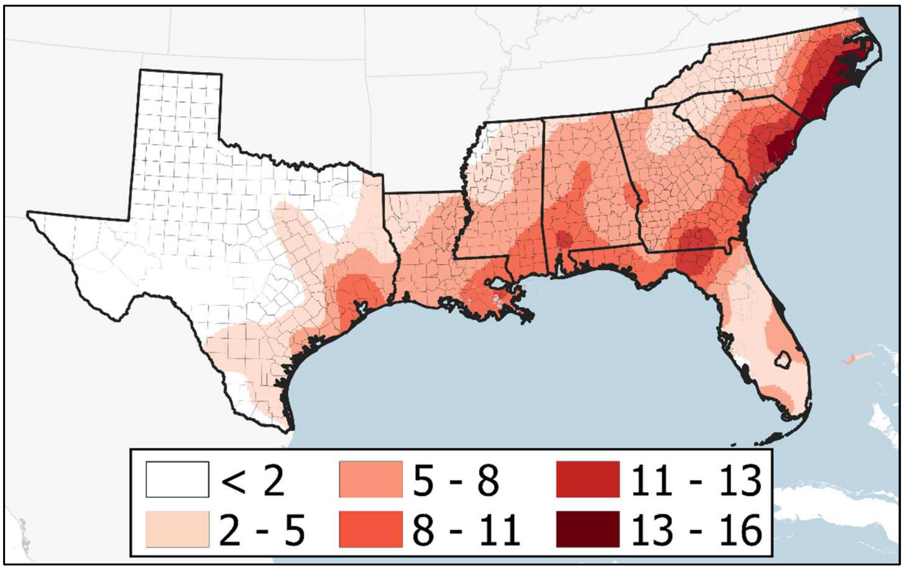

Fig. 2. Kernel density of all tropical cyclone center tracks used in this study (1986–2021). Cropland represented by outlined counties with darker outlines representing higher production. (*Color not needed for print*)

2.4. Soil moisture data

Palmer Modified Drought Index (PMDI) data were used as a measurement of soil moisture (NWS, 2011). The PMDI attempts to measure the duration and intensity of long-term drought-inducing circulation patterns and is the operational version of the Palmer Drought Severity Index (PDSI). Long-term drought is cumulative, so the intensity of drought during the current month is dependent on the current weather patterns plus the cumulative patterns of previous weeks, but the PMDI can respond fairly rapidly even if it cannot totally capture the instance of flash droughts (Palmer, 1965; NCEI, 2021). Therefore, PMDI values were collected for each report for the week prior to a TC impacting the cropping area (week 0). PMDI values greater than or equal to 2.0 represented "wet" conditions in this research, values less than or equal to -2.0 represented "dry" conditions, and values between -1.99 and 1.99 represented near normal conditions (Palmer, 1965). These data are available at the climate division level (NOAA, 2022), thus, PMDI data were gathered only for the divisions that were impacted by the circulation center of the TC represented in **Fig. 2** and if there was crop production in that division at the time of the TC. These data were then averaged for each state to inform the precursor PMDI value/classification for each TC case. In addition, the soil moisture analysis was separated into different portions of the growing season: May and June represented the early portion of the growing season, July and August represented the middle portion, and September and October represented the late portion.

2.5. Analysis

Crop condition data were gathered for the week before TC impact (week 0), the week of the TC impact (week 1), and the week after the TC impact (week 2). Week 1 and week 2 represent the impacts TCs may have on crops. These two weeks were collected as extension agents conducting the crop condition survey may see more of the possible slower developing impacts from the TC in week 2, or perhaps, more recovery. Also, it is possible that week 2 may be the only time to adequately assess the crop in severe cases where more direct results of the TC may have needed to be dealt with first during week 1 or immediately after the TC. All in all, assessing the week of the TC impact and week after will likely represent most of the effects TCs bring upon crops while limiting the potential weather effects after the TC. The percent change for each condition category (excellent, good, fair, poor, very poor) was calculated between week 1 and week 2 from week 0. The weekly change value amongst the crop condition categories represents one report. A single TC can have multiple reports depending on the intensity changes, and how many states/crops it impacts. For example, Dennis in July 2005 has six different reports as outlined below:

- Category 3 Hurricane Dennis affected 1) Florida peanuts.
- Downgraded to a tropical storm and affected 2) Alabama cotton and 3) Alabama peanuts.
- Further downgraded to a tropical depression and affected 4) Mississippi cotton, 5) Mississippi rice, and 6) Mississippi soybean.

In total, there were 534 reports each for week 1 and week 2, making the entire dataset consist of 1068 reports. To examine changes, or differences between crop condition movements, a combination of three assessments were made. This includes 1) computing how many reports/cases resulted in a decrease or increase in excellent, good, fair, poor, very poor condition, and then ultimately the CCI, 2) visually assessing the interquartile distribution of the box and whisker plots for each condition, and 3) computing the statistical differences between the averages in each condition change. To determine this third step, the Tukey HSD ("honestly significant difference") multiple comparison test was computed at the 95% confidence level. Tukey HSD determines if the relationship between two sets of data is statistically significant in terms of their difference in means (Ott and Longnecker, 2015). The TukeyHSD test results are presented in the Appendices section.

For yield assessment, week 1 and week 2 CCI was averaged and used within each state/crop's unique least squares regression equation to model weekly crop yield. The least squares regression equation was computed based on the annual average CCI which has been proven to be a useful metric when quantifying crop yield throughout the growing season (Bundy and Gensini, 2022). The model equation for this portion of the analysis is specified below (Equ 2):

$$\mathrm{Yield}_{\mathrm{Est}} = \widehat{\beta_1} \cdot \mathrm{X} + \widehat{\beta_0} \qquad 2$$

where $\widehat{\beta_1}$ is the least squares regression slope, X is the current week's CCI, and $\widehat{\beta_0}$ is the Y-intercept of the regression equation. If the coefficient of determination was not statistically significant to the 95% confidence level, then those yield data for the respective state and crop were not used. States and crops not used in the yield analysis included Texas cotton, Texas rice, Mississippi corn, Mississippi rice, Mississippi peanuts, Florida cotton, and South Carolina Peanuts, which consists of 13% of the reports (67 of 534). Yield was modeled based on the CCI for week 0 and the average of week 1 and week 2 CCI to determine the yield change percentage. Yield change percentages were also calculated between week 0 and the actual end of year yield.

3. RESULTS

3.1. Condition changes by crop

The largest movements in week 1 and 2 coverage changes were reflected in crops considered in good and fair condition (**Fig. 3**). This is in large part due to crops considered in good condition represented nearly half the total crop area across the Coastal Southern U.S., while conditions considered fair represented 30% of the total crop area on average since 1986 (USDA, 2022). Thus, with over 3/4 of a given crop area for each state in good or fair condition, it is more likely for these conditions to have some of the most notable weekly changes after any weather hazard impact. For most crops after TC impact in weeks 1 and 2, the decrease on average for excellent and good conditions resulted in an increase in fair conditions, and to a lesser extent, an increase in poor and very poor conditions. This is supported by a Pearson correlation coefficient average between excellent versus CCI and good versus CCI of 0.63, and an average Pearson correlation coefficient between fair versus CCI, poor versus CCI, and very poor versus CCI of -0.56. Both correlations are considered large in terms of the strength of the relationship (Cohen, 1988). In other words, crops that were considered optimal for normal or above normal yield potential (excellent or good conditions) were downgraded to a condition where yield loss is a possibility (fair conditions) or downgraded to a condition more conducive of a heavier degree of loss to yield potential (poor or very poor). Consequently, this resulted in a marginal decrease in the CCI up to 4% on average for all crops in week 1 and week 2. For corn, cotton, peanuts, rice, and soybeans, the average decrease good conditions for weeks 1 and 2 were consistent between 3–5% (**Figs. 3a, 3b, 3c, 3d, 3f**). For these crops that were in fair or poor condition, averages were somewhat variable from crop-to-crop, with resulting increases up to 3%. Differences in averages between changes in good and fair conditions were statistically significant at the 95% confidence level for cotton, rice, and soybeans (Appendix C). Between good and poor or very poor conditions, the differences in average changes were statistically significant for all crops except corn and sorghum (Appendix C). Sorghum was the only crop to not follow the general decreasing good condition and increasing fair and poor condition (**Fig. 3e**). Conditions for sorghum were generally unchanged until week 2 when good condition coverage increased and fair condition coverage decreased on average. The distribution for both weeks, though, favored an increase in good conditions and a decrease in fair conditions.

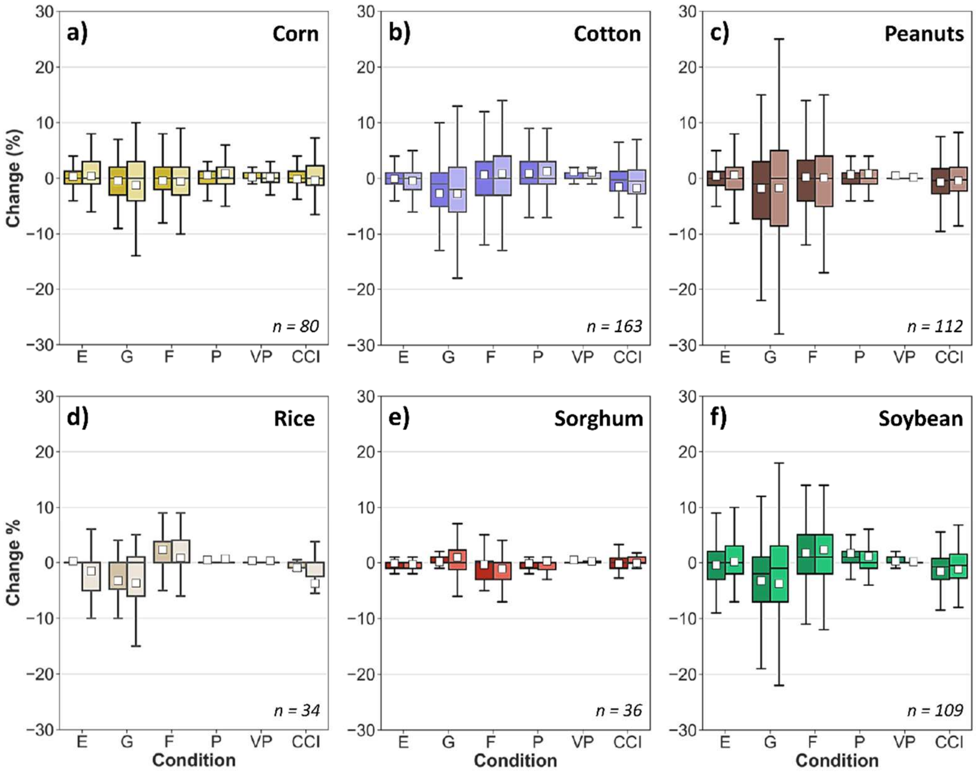

Fig. 3. Box and whisker plots of all week 1 (darker hue) and week 2 (lighter hue) deltas from week 0 for each condition after a tropical cyclone impacted the respective crop area. Each box and whisker present a six number summary: whiskers represent the 1.5 multiple of the inner-quartile range (outliers considered but not included in plots); boxes represent first quartile (25th percentile) and third quartile (75th percentile) values; black line horizontal within boxes represent the median value; white squares represent the mean value. (*Color not needed for print)*

For these crops that were in fair or poor condition, averages were somewhat variable from crop-to-crop, with resulting increases up to 3%. Differences in averages between changes in good and fair conditions were statistically significant at the 95% confidence level for cotton, rice, and All crops analyzed in this research displayed a decrease in the CCI on average and did not have statistically significant differences between condition changes when comparing each crop and condition combination (Appendix D), which suggests a generally homogenous reaction amongst crops to TC impact even with the differences in sample size (**Table 1**). Therefore, the similar CCI changes to TC impacts justifies aggregating all crops in this research together for analysis in the following sections.

While the average changes in crop conditions do display statistical differences amongst the different condition categories, the entire distribution of the box and whiskers need to be discussed as there is a considerable amount of variability in terms of weekly changes. Hence, the result of a TC impact on crop conditions did not always result in detrimental changes. In fact, only half of the cases overall resulted in a decrease in the CCI. As a whole, weekly changes in good conditions possessed a standard deviation of nearly 10%, while fair was 8% and the remaining conditions (excellent, poor, very poor) ranged between 3–5%. This suggests that other factors (e.g., time of season, TC strength, precursor soil moisture) may contribute significantly to variability across all crops.

3.2. Condition changes by month

Based on the timing of a TC with respect to the phenological stage of the crop, examining condition changes by month revealed essential information regarding the timing risk of TC impacts on agriculture (**Fig. 4**). When aggregating all crops examined in this study together, the month of May showed only marginal evidence of an improvement in conditions (**Fig. 4a**). This is supported by a decrease in good and fair conditions while there was a subtle increase in excellent, poor, and very poor conditions; overall these subtle changes did not lead to any net change in the CCI on average. However, the median change and overall interquartile distribution does favor marginal improvement. In addition, 68% of the cases resulted in an increase in the

CCI during May. TCs resulted in subtle improvements in crop conditions overall in June and July as well (**Figs. 4b, 4c**). This is reflected in the CCI changes in week 1 and week 2, which increased up to 2% on average. Notably, conditions considered fair were upgraded to good or excellent in June and July as the differences in averages for good/excellent conditions were statistically different than fair and poor conditions (Appendix E).

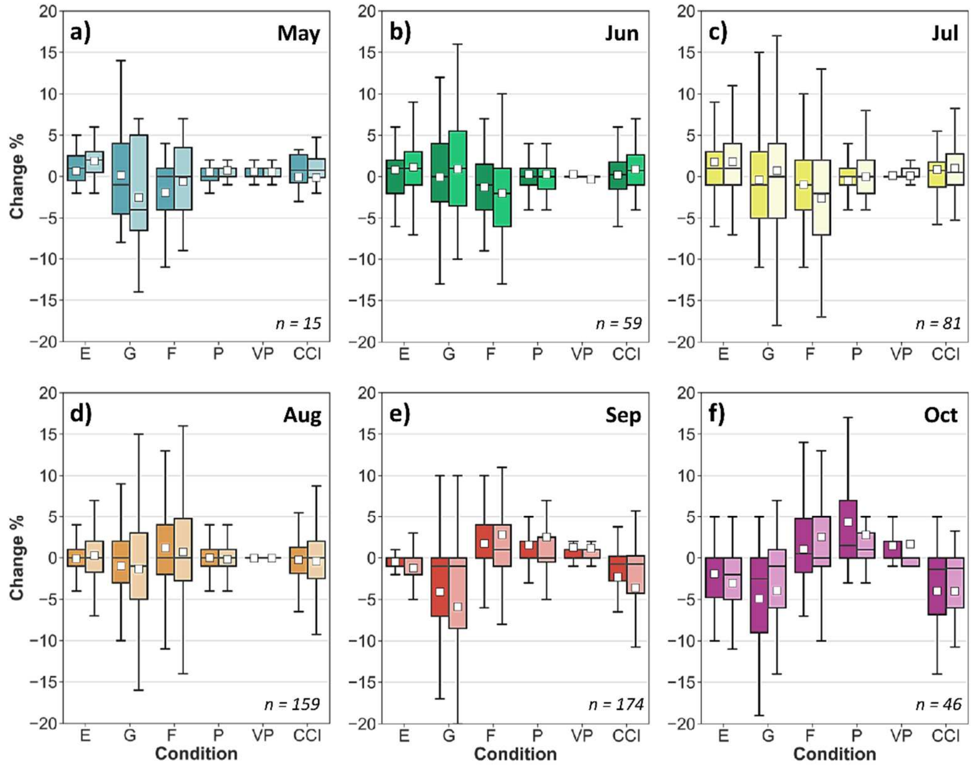

Fig. 4. Box and whisker plots of all week 1 (darker hue) and week 2 (lighter hue) deltas from week 0 for each condition after tropical cyclone impact separated by month. Each box and whisker present the same six number summary as described in Fig. 3. (*Color not needed for print)*

For both months, 60% of the cases resulted in an improvement in crop conditions. For August, CCI was practically unchanged in week 1 and week 2 with no statistically significant differences between condition averages. Also, nearly half of the cases resulted in an increase or decrease in crop conditions, and thus, there was not strong evidence to support any major change in crop conditions due to TC impact in August.

August served as somewhat of a transition period for change in crop conditions. In the latter portion of the growing season, September and October displayed the largest movements in crop conditions, suggesting these two months are the most important for crop conditions when it comes to TC impact (**Figs. 4e, 4f**). This is especially true in the good and fair condition movements as, on average, weeks 1 and 2 good conditions decreased by nearly 5% while fair conditions increased by 1–3%. In addition, excellent conditions decreased on average by up to 3% while poor and very poor conditions increased between 2–4% on average for both week 1 and week 2 changes. The changes in excellent and good conditions for week 1 and week 2 within September and October were statistically significantly different than the changes in fair, poor, and very poor conditions with 95% confidence (Appendix E). When comparing September and October with May, June, July, and August, statistically significant differences across condition changes were observed (Appendix F). The result for both months was a decrease in the CCI by 3–4%, which was the strongest crop condition change signal for the growing season. This is also supported by both interquartile ranges for these months being at or below 0 for the CCI with nearly 66% of cases resulting in a decline in crop conditions.

Even when aggregated by month, there was still a respectable amount of variability. Still, monthly aggregation was a statistically significant predictor of crop condition changes after TC impact, suggesting crop phenology is important when assessing the specifics of TC impacts on field crops in the Coastal South.

3.3. Condition changes by tropical cyclone intensity

In addition to growing season timing, TC intensity also plays a significant role in crop condition changes. Overall, the strength of a TC was the most statistically significant predictor of crop condition changes when including all variables. When all crops are aggregated together, tropical depressions and tropical storms did not tend to impact average conditions (**Figs. 5a, 5b**). Furthermore, the average CCI had nearly 0% change in both weeks 1 and 2, and there were no statistically significant differences between the averages of condition changes (Appendix G).

Once TCs reached hurricane status, noteworthy changes in conditions were observed as statistically significant changes between excellent/good and fair/poor/very poor were observed (Appendix G). For category 1 and category 2 hurricanes, crops rated in good condition decreased in week 1 and week 2 between 5–8%, which consequently resulted in an increase in fair, poor, and very poor condition coverage ranging between 1–4% on average (**Figs. 5c, 5d**). The interquartile distributions of the box and whisker plots for both category 1 and 2 hurricanes were near or below 0% change in excellent and good conditions. Meanwhile, the interquartile distribution for poor and very poor conditions were near or above 0% change. As a result, the CCI interquartile distribution was at or below 0%. Nearly 66% of all cases resulted in a decrease in crop conditions after category 1 or 2 hurricane impact. When hurricanes reached "major hurricane" status at category 3 or higher, the resulting detrimental crop condition changes were more substantial (**Figs. 5e, 5f**).

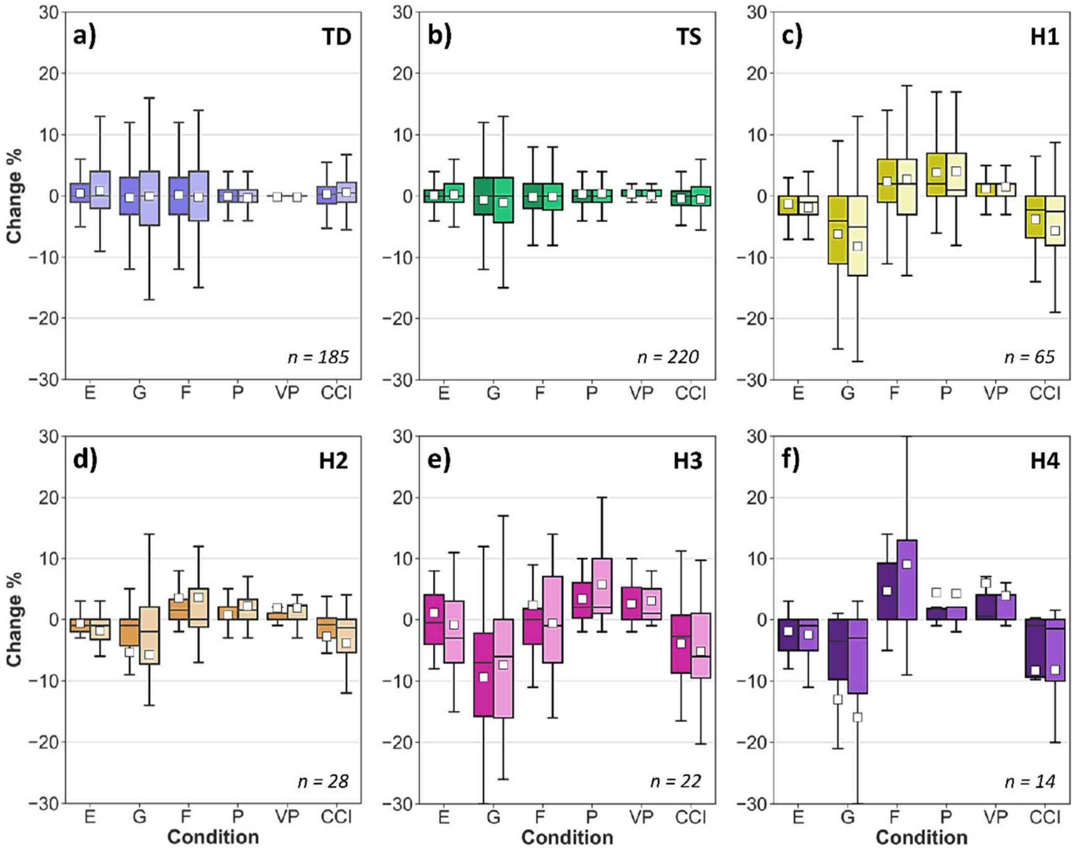

Fig 5. Box and whisker plots of all week 1 (darker hue) and week 2 (lighter hue) deltas from week 0 for each condition after tropical cyclone impact separated by tropical cyclone strength. Each box and whisker present the same six number summary as described in Fig. 3. (*Color not needed for print)*

As is the general trend with the other results, a general decrease in excellent and good conditions resulted in an increase in fair, poor, and very poor conditions for category 3 and category 4 hurricane impacts. For category 3 hurricanes, the decrease in good conditions in week 1 neared 10%. This decrease was even higher for category 4 hurricanes (13%). As a result, the CCI decrease after being impacted by category 3 or category 4 hurricanes was near 5% and 9%

respectively for both week 1 and week 2. In total, 70% of the cases for category 3 hurricane impact resulted in a decline in crop conditions while 83% of the category 4 hurricane cases resulted in a decline. The interquartile distribution for category 3 and 4 hurricanes was also similar to category 1 and 2 impact, which further emphasizes the significant relationship between TC strength and crop condition changes. Also, when comparing the changes for each condition with each TC strength combination, statistically significant differences were noted when comparing the condition changes for hurricanes against tropical storms and depressions (Appendix H).

3.4. Condition changes under precursor soil moisture conditions

Soil moisture conditions prior to TC impact along with the time of the growing season also plays a vital role in whether crops may benefit from TCs. For instance, during certain phenological stages of crop development, depending on the status of the crop (e.g., dry, wet), TCs may yield positive or negative impacts on crop conditions (**Fig. 6**). Precursor (week before TC impact) PMDI conditions were also a statistically significant predictor of crop condition changes. Under precursor PMDI conditions considered wet (PMDI $\geq$ 2.0), on average, crop conditions did not improve in any part of the growing season (**Figs. 6a, 6b, 6c**). In the early portion of the growing season (May and June), TCs negatively impacted crop conditions when precursor PMDI conditions were wet (**Fig. 6a**). Thus, fields that were at least already at least moderately moist and became saturated after a TC did not typically improve the quality of the crop. This is supported by the statistically insignificant differences between excellent and good conditions compared to fair, poor, and very poor conditions to the 95% confidence level (Appendix I). During the middle portion of the growing season, there was no statistical support to suggest TCs improve or deteriorate crop conditions, on average (**Fig. 6b**; Appendix I).

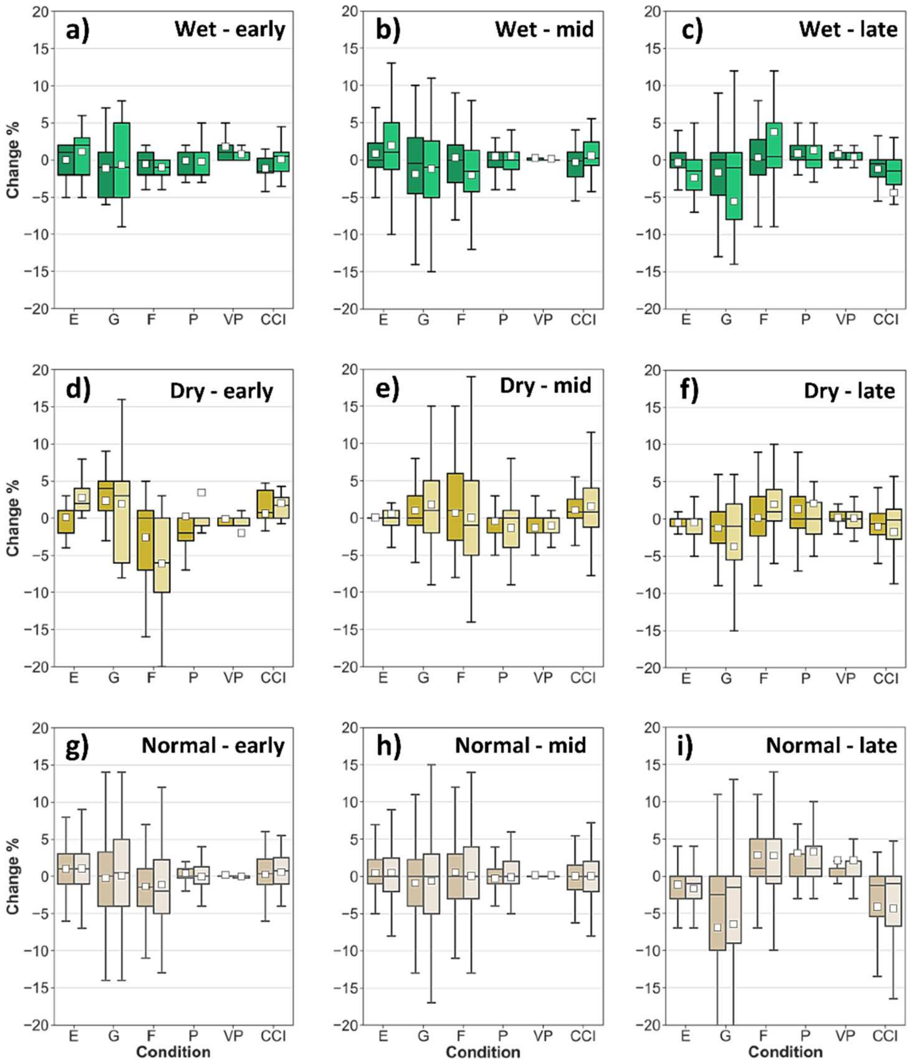

Fig. 6. Box and whisker plots of all week 1 (darker hue) and week 2 (lighter hue) deltas from week 0 for each condition after tropical cyclone impact separated precursor soil moisture condition and seasonal timing. Each box and whisker present the same six number summary as described in Fig. 3. (*Color not needed for print)*

Therefore, if precursor soil moisture conditions were already optimal during the critical reproduction period of the growing season, conditions remained stable after a TC impact.

By the latter portion of the growing season under wet precursor conditions, crops under excellent or good conditions decreased in coverage resulting in an increase in coverage of crops in fair, poor, or very poor condition on average (**Fig. 6c**). This was supported by the statistically significant differences between excellent (more so in week 2) and good conditions compared to fair, poor, and very poor conditions (Appendix I). As a result, the decline in favorable conditions resulted in a decrease in the CCI for both week 1 and week 2 on average by 2–4%.

Under dry precursor soil moisture conditions, or conditions that are at least considered in a moderate drought (PMDI $\leq$ -2.0), TCs did benefit crop conditions overall in the early and middle portions of the growing season (**Figs. 6d, 6e**). This was reflected by subtle differences between excellent with good conditions as compared to fair conditions in the early portion of the growing season, which resulted in a CCI increase between 1–3%. During the middle portion of the season, the greatest movements were observed in good conditions (increase in coverage) and in poor and very poor conditions (decrease in coverage) resulting in a CCI increase between 2–3%. However, by the latter portion of the growing season, even under drought conditions, TCs caused crops that were in excellent and good condition tend to be downgraded to fair and poor condition on average (**Fig. 6f**). These were the only changes in the growing season under dry precursor soil moisture conditions that were statistically significant to the 95% confidence level (Appendix I). The result was a decrease in the CCI between 2–3%.

Near-normal precursor soil moisture conditions were present in 63% of the cases in this study. When these conditions were present prior to TC impact, after the TC, crop conditions generally remained stable on average as there were no statistically significant differences between conditions for week 1 and week 2 in the early and middle portion of the growing season (**Figs. 6g, 6h;** Appendix I), resulting in no change to CCI. It was not until the latter portion of the growing season when conditions that were excellent or good downgraded to fair, poor, or very poor condition on average, with CCI decreases of nearly 5% (**Fig. 6i**). When comparing the total crop condition changes (CCI) for all precursor soil moisture conditions and timing, statistically significant differences were noted between near normal and wet precursor conditions in the latter portion of the growing season versus the early and middle portions (Appendix J).

3.5. Yield changes

When working with USDA crop condition data, an essential component to the communication and interpretation of the data is how yields respond to variations in the CCI (Bundy and Gensini, 2022). This is a crucial part of the analysis as not only does further the understanding of yield responses to tropical cyclones, it also confirms the use of the USDA crop condition dataset for in season risk assessment and future analyses. As the CCI increases, yield prospects generally increase as well across most crops and states analyzed in this research (**Fig. 7**). There is a varying level across all crops and states of how much the CCI can explain variability in yield, and therefore, should be used in practice with caution. Corn tends to have the strongest correlation between CCI and yield as the average coefficient of determination in the Coastal Southeast U.S. region is 0.63, with South and North Carolina possessing the highest coeffients of determination for any state-crop combination at 0.87 and 0.80, respectively (**Fig. 7a**). The next strongest relationship between crop condition ratings (CCI) and yield is for soybeans across the region as the average coefficient of determination is 0.44. Similar to corn, states along the Atlantic Ocean coast possess the stronger connection between the CCI and soybean yield (Georgia, South Carolina, North Carolina) versus states along the Gulf Coast (Texas, Louisiana, Mississippi, Alabama; **Fig. 7f**). Cotton, peanuts, and sorghum all have similar relationships between CCI and yield with coefficient of determination averages for the region of 0.35, 0.33, and 0.38, respectively (**Figs. 7b, 7c, 7e**).

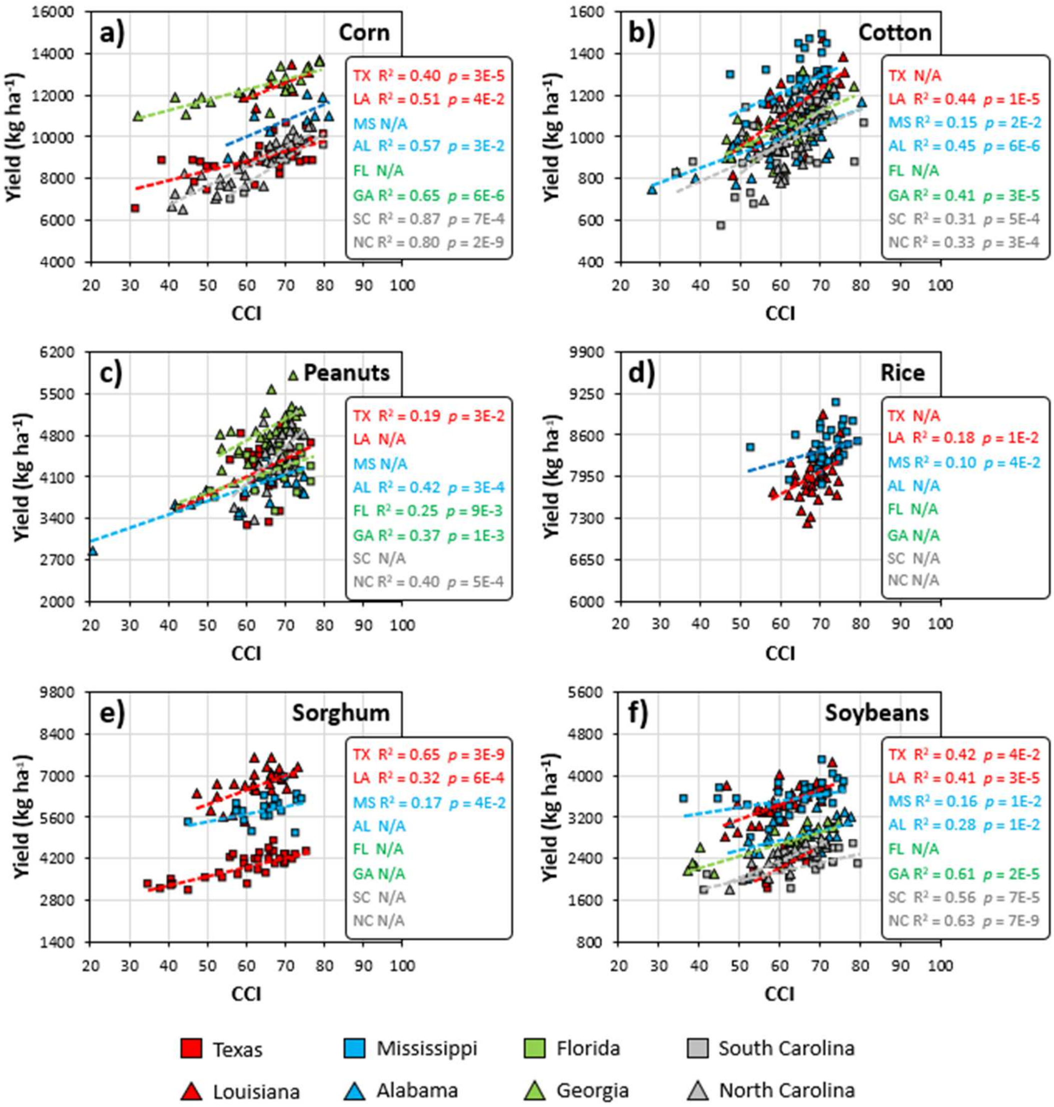

Fig. 7. Annual average Crop Condition Index (CCI) values plotted against annual yield values for each state paneled by crop in the Coastal Southern U.S. region: a) corn, b) cotton, c) peanuts, d) rice, e) sorghum, f) soybeans. Regression r^2 and *p* values are listed next to their respective states.

Rice is the lowest in terms of the CCI relationship with yield as the coefficient of determination average in the region is 0.14. Nonetheless, the CCI can still explain a statistically significant (95% confidence level) amount of the variability in rice yield. The specific linear model equations for each regression line in **Fig. 7** can be utilized from Appendix K.

Between each crop, yield changes were generally homogeneous (**Fig. 8a**). Statistically, there were no significant differences between each of the respective crops for after the TC and for end of year yield to the 95% confidence level (Appendix L). After a TC, modeled yield changes were marginal as changes ranged between -1–1% on average for each crop.

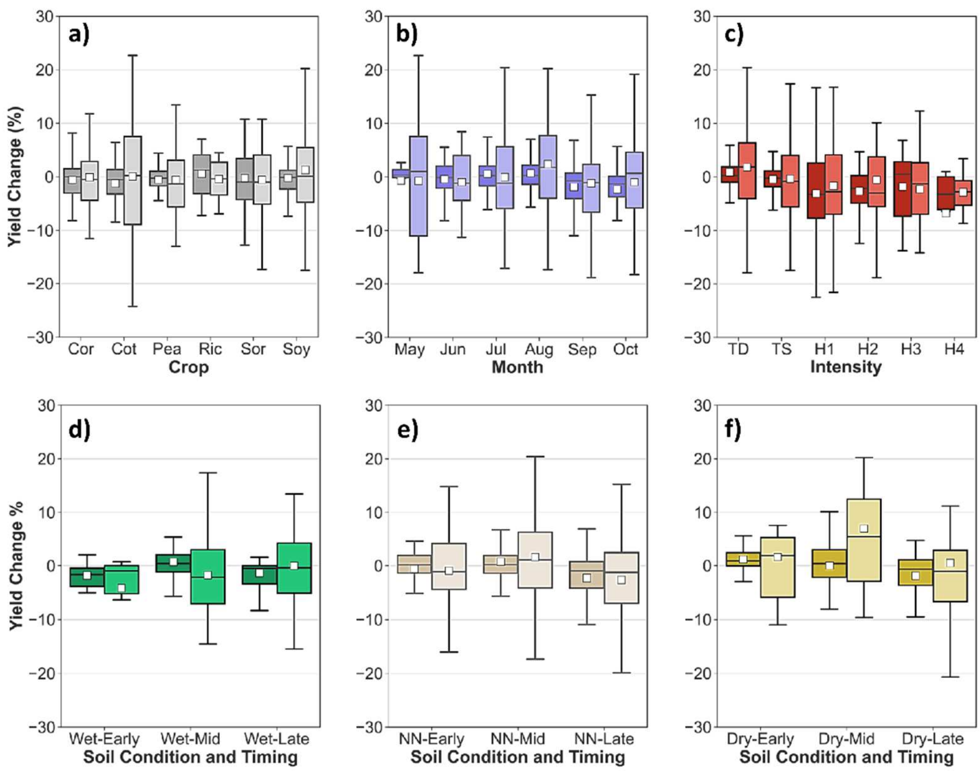

Fig. 8. Change in yield percentages one week after a tropical cyclone impacts a cropping area (darker hue) and the difference between the yield forecast and actual yield (lighter hue) paneled by cropping type, month, intensity, and soil condition and timing. Each box and whisker present the same six number summary as described in Fig. 3. (*Color not needed for print)*

The same holds true for end of season yield as each crop displayed only marginal changes ranging between -1–2% (**Fig. 8a**). When examining end of season yield, variability was much greater compared to modeled yield changes after the week 1 and week 2 average changes due to improvements in conditions or worsening conditions after TC impact (based on the remainder of the growing season's weather conditions).

Aggregating all crops together for the yield analysis, the percentage changes were aggregated together rather than the actual yield numbers to avoid production biases. When all crops were aggregated together and examined on a monthly interval, September and October compared to July and August were the only months in which the average change in modeled yield percentages after TC impact were statistically different (**Fig. 8b**; Appendix L). Within September and October, average modeled yield changes between week 1 and week 2 crop conditions resulted in about a 3% decrease in yield. Actual end of year yield changes amounted to a 2% decrease in yield within September and October. When examining yield response by TC intensity, modeled yield changes as well as end of year yield changes tended to increasingly worsen on average as the TC intensity increases (**Fig. 8c**). After tropical depression impact, yield tended to slightly improve for both modeled changes and actual end of year changes (+1–2%). On average, tropical storms did not tend to impact yield in any direction. Once hurricane status was reached, modeled yield changes decreased between 3–6% after TC impact, and end of year yield numbers also decreased 1–3%.

When examining yield response to TC impacts based on precursor soil moisture conditions (**Figs. 8d, 8e, 8f**), the trend was generally the same as the crop condition responses. Thus, under wet precursor conditions during the early and latter portion of the growing season resulted in modeled yield changes and to an extent, end of year yield changes to decrease on average by 1–5%. Under near-normal precursor soil moisture conditions, yield decreased during the latter portion of the growing season on average after TC impact by 3–4%. Under dry conditions, TCs tended to improve yield during the early and middle portions of the growing season while decreasing yield in the latter portion of the growing season by up to 2% on average.

From and event by event standpoint, the top five TCs based on the crop condition changes and yield changes after the TC all had common attributes (**Table 2**). These TCs had a maximum strength of tropical depression or tropical storm and occurred in August or earlier.

Table 2. Top five most beneficial and detrimental tropical cyclone events based on crop condition and yield projection response (1986-2021). Crop Condition Index (CCI) Change, Yield Change, and End of Year Yield Change were averaged across all states and crops examined for the tropical cyclone. No ranking is established in this table.

Tropical Cyclone Events Beneficial for Crops

Name	Max Strength	Dates	Crops	States	CCI Change	Yield Change	End of Year Yield Change
Danny 1997	TS	7/21 - 7/24	Cor, Cot, Pea, Soy	AL, FL, NC, SC	4.1%	6.3%	3.5%
Beryl 1988	TD	8/10 - 8/10	Cot, Ric, Sor, Soy	LA	1.8%	7.6%	9.7%
Isaias 2020	TS	8/4 - 8/4	Cor, Cot, Pea, Soy	NC	4.0%	5.3%	-1.6%
Jerry 1995	TD	8/25 - 8/27	Cor, Cot, Soy	GA	4.7%	4.0%	6.6%
Cindy 2005	TD	7/6 -7/7	Cot, Pea	AL	5.8%	3.5%	-0.8%

Tropical Cyclone Events Detrimental for Crops

Name	Max Strength	Dates	Crops	States	CCI Change	Yield Change	End of Year Yield Change
Hugo 1989	H4	9/22 - 9/22	Cor, Cot, Soy	NC, SC	-23.1%	-18.6%	-3.9%
Floyd 1999	H1	9/16 - 9/16	Cor, Cot, Pea, Soy	NC	-12.0%	-16.2%	-13.9%
Fran 1996	H3	9/6 - 9/6	Cor, Cot, Pea, Soy	NC	-9.0%	-10.9%	-3.9%
Matthew 2016	H1	10/8 - 10/8	Cot, Pea, Soy	SC	-12.9%	-9.9%	-12.5%
Ivan 2004	H3	9/16 - 9/17	Cot, Pea	AL	-11.3%	-7.4%	0.9%

In addition, four of the five TCs went over cropland area with precursor PMDI values near-normal or drier than normal. On average, the range of CCI increase for these top events averaged across the study domain and across all crops was a 1.8%–5.8% increase while the modeled yield chances after the TC ranged between an increase of 3.5%–7.6%. Not all the top events resulted in a yield increase by the end of the growing season though, which is due to potential weather impacts after the TC that resulted in a decline in crop conditions and yield. For the TC events that were most detrimental to crops in the Coastal Southern U.S. region, another pattern is established in that the maximum strength of the TC reached hurricane status and occurred in September or later. Precursor soil moisture values were mixed for these events as they ranged from drier than normal to wetter than normal. Category Four Hugo in 1989 resulted in a regional average CCI decrease of 23.1% and yield prospect decrease of 18.6%. Though the largest end of year yield decrease (13.9%) came with Category One Floyd in 1999 that impacted four different crops in North Carolina. Since 1986, four of the five most detrimental TC events to crop conditions and yield across the study region occurred in North and South Carolina.

4. DISCUSSION

Within the 36-year (1986–2021) study period, impacts of TCs were both positive and negative for overall crop quality and yield. In response to local topography, soils, land use, access to transportation, and weather patterns, agriculture in the Coastal South U.S. is highly heterogeneous (Knox et al. 2014). This is somewhat in contrast to what was quantified in this study as analysis of variance indicated that there were no statistical differences amongst field crop responses to TCs (**Fig. 3;** Appendix D). However, this study examined the effects of TCs since 1986 across eight states using state-level data for six field crops, which was previously noted as a limitation to this work. In other words, the publicly available state-level data may not be able to capture the heterogeneities the Coastal Southern U.S. agricultural region possesses, especially since hybrid characteristics can influence the rate of grain drying become more important during unfavorable conditions such as a TC (Troyer and Ambrose, 1971; Cavalieri and Smith, 1985).

The latter portion of the growing season is critical for crop quality and yield impacts from TCs as some of the most notable negative changes were observed in September and October (**Figs. 4e, 4f, 6c, 6f, 6i, 8b, 8d, 8e, 8f**). These negative changes in crop conditions and crop yield can be attributed to a few nontrivial factors. The point made about grain drying seems to be an essential one given the overall negative crop quality and yield reactions to TCs in the latter portion of the growing season. Harvest time, which runs from late August through late October for the field crops examined in this study, is a period when dry conditions are more favorable for crop quality. Before harvest, grain crops need to undergo a drydown period to achieve maturity and begin harvest, making this important for maximizing yield (Coulter, 2008; Nielson, 2018). For example, ideal harvest moistures for corn ranges from 15–20%, or higher (Elmore and Abendroth, 2010). Delaying harvest until corn dries increases the risk for frost damage, and fields with poor stalk quality become increasingly susceptible to stalk lodging (Cleugh et al. 1998; Lindsey et al. 2021). As a result, harvest efficiency decreases and the potential for significant yield loss increases. The same can be said about other crops in this analysis including cotton, rice, sorghum, and soybeans where a critical drydown period is essential for maturity, harvest, and maximizing yield (Philbrook and Oplinger, 1989; Zhang et al. 1996; Elmore and Roeth, 2013; Kebebe et al., 2015). On the other hand, peanut crops need adequate moisture before harvest so that plants do not get pulled off the vines and then are left in the ground as a result of drier conditions. For cotton, too much moisture from rainfall as seeds inside the bolls get too wet and start sprouting, consequently, reducing the quality and yield (Zuberer and Kenerley, 1993; Landivar and Benedict, 1996; Mailhot et al., 2012). In addition, peak harvest time is concurrent with peak TC frequency in the Coastal Southern U.S.; thus impacting 1) soil moisture in fields making them difficult for machinery to harvest the crop, and 2) as mentioned, the quality of crops that require ample drying time during maturity (Knox et al., 2014; Nielson, 2018). This may also explain why TCs did not show any evidence of improving crop conditions even when precursor soil moisture conditions were considered dry during the latter portion of the season (**Fig. 8f**). On the other hand, TCs did act to improve overall crop conditions and crop yield prospects in the early and middle stages of the growing season (**Figs. 4b, 4c, 6d, 6e, 8b, 8e, 8f**) due to crops requiring adequate soil moisture during the developing and reproductive stages in the phenological cycle. Therefore, TCs do provide some benefits to crops if the timing is correct.

Analyzing crop condition response with TC classification, or intensity, also presented results that were to be expected when considering increased wind speeds with higher classifications. That is, the greater the intensity, the higher likelihood of a decrease in optimal crop conditions (**Fig. 5**). As noted, this can be explained in part by the increase in winds with an increase in TC intensity category, as stronger winds create a higher likelihood of greensnap and root lodging. In addition, a statistically significant positive correlation has been found between maximum wind speeds in TCs with average TC-induced rainfall totals (Cerveny and Newman, 2000). Though, this correlation is not always clear, and future work may examine the impacts TCs have on agriculture based on rainfall totals. This would require a higher resolution crop condition dataset, such as the recently released gridded crop condition dataset by the USDA

NASS which dates to 2015 (Rosales, 2021). The result was a greater decrease in crop condition ratings conducive of optimal yield potential. Excess rainfall at any point in the growing season can cause physical damage to crops by ponding and waterlogging which can lead to root rot, soil erosion and salinity, and sprouting of grains, which ultimately can lead to a reduction in optimal crop condition coverage and potentially a reduction in yield (Li et al., 2019; Bundy and Gensini, 2022). In addition, the strongest TCs are favored during the latter portion of the growing season (NHC, 2022). This is important because TCs during the latter portion of the growing season not only can cause greensnap and root lodging, but waterlogging can prevent field work operations during the harvest period.

In terms of resilience, agricultural producers and other stakeholders need climate data and information such as the results of this study due to the importance of decision making and adaptation strategies (Changnon, 2007). Furthermore, the interactions among producers and meteorologists plays a critical role in increasing the integration and use of climate knowledge for adaption (Brugger et al., 2016). Such adaptation strategies can be in the form of shifting production systems, investing in crop insurance, or advancing in crop management, technologies, and/or hybrids that are more resilient to the potential detrimental effects TCs have on crop conditions.

5. CONCLUSIONS

The Coastal Southern U.S. is uniquely vulnerable to tropical cyclone (TC) impacts during each growing season. Statistically significant differences between crop condition categories revealed that TCs do have a notable impact on agriculture in this region. The overall tendency is for crops in excellent and good condition to be downgraded to fair, poor, and very poor condition after a TC impact. Corn, cotton, peanuts, rice, sorghum, and soybean displayed similar condition changes after TC impact, and thus, were aggregated together since crop type was not a statistically significant predictor of condition changes. TC intensity was the most statistically significant predictor of crop condition changes in the Coastal Southern U.S. Crops were most negatively impacted when 1) crops are in the latter portion of the growing cycle thus requiring drier conditions for maturity and fieldwork operations, 2) the TC reached major hurricane status, and 3) when precursor soil moisture conditions were in any state of surplus in the latter portion of the growing season. Consequently, yield prospects decline after a TC based on the declines in coverage of excellent and good conditioned crops (yield declines of 1–6% on average); though, crop conditions tend to recover resulting in yield prospects to also recover to a marginal extent by the end of the season (declines of up to 3%). Overall, the statistics presented in this study provide a general overview of crop quality and crop yield responses to TCs, which had not been quantified to this point in literature. Quantifying these week-to-week changes in crop condition ratings after TC impact provides risk assessment information for agricultural producers in this region. This may aid in the decision-making process regarding crop management and protection, potentially in the form of insurance, especially during critical periods such as harvest in order to maximize revenue. Under a changing climate, uncertainty in TCs trends further emphasizes the need for resilience and mitigation efforts in order to ensure a more sustainable agricultural system in the important agricultural sector that is the Coastal Southern U.S.

ACKNOWLEDGEMENTS

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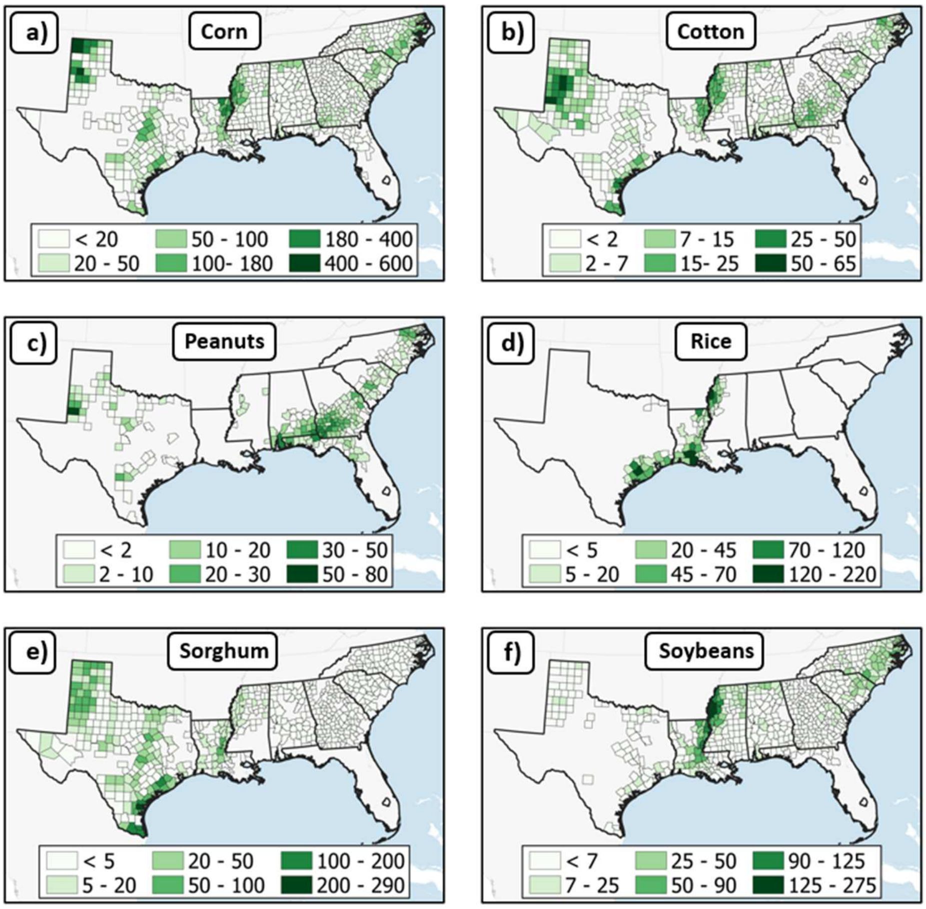
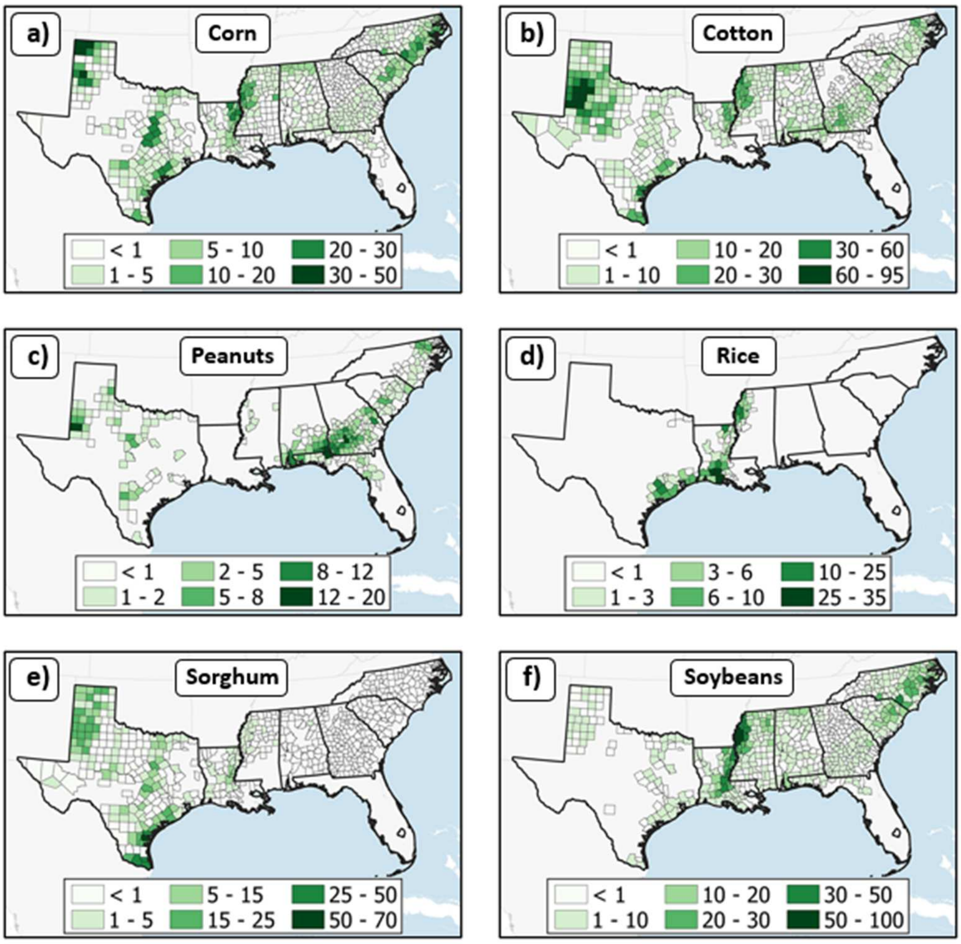
DATA STATEMENT

All data are publicly available for download and use through the United States Department of Agriculture National Agriculture Statistics Service's Quick Stats website, National Oceanic and Atmospheric Administration's Historical Hurricane Tracks website, and National Weather Service Climate Prediction Center's Drought Monitoring website.

APPENDICES



Appendix A. Average annual production (kg in millions) at county-level for each crop examined in the Coastal Southern U.S. region (1986–2021). Locations within the study area without a county outline did not have any production for the respective crop. (*Color not needed for print)*



Appendix B. Average annual acreage (ha in thousands) at county-level for each crop examined in the Coastal Southern U.S. region (1986–2021). Locations within the study area without a county outline did not have any production for the respective crop. (*Color not needed for print)*

Appendix C. TukeyHSD multiple comparisons results between each condition combination by crop for both week 1 and week 2. Table displays the differences between the means along with the corresponding p values. Bolded text represents statistical significance at 0.05 significance level.

	Corn				**Cotton**				**Peanuts**				**Rice**				**Sorghum**				**Soybeans**			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
F-E	-0.73	0.818	-0.81	0.95	0.76	0.884	1.28	0.639	-0.15	1	-0.49	0.998	0.48	0.998	3.52	0.201	-0.28	0.998	1.71	0.667	2.19	0.147	2.14	0.367
G-E	-0.75	0.796	-1.64	0.502	**-2.56**	**0.003**	-2.28	0.07	-2.21	0.128	-2.31	0.284	**-3.70**	**0.041**	-2.25	0.854	0.28	0.998	0.91	0.988	**-2.79**	**0.025**	**-3.89**	**0.005**
P-E	0.25	0.998	0.74	0.929	0.97	0.731	1.71	0.316	0.31	0.999	0.21	1	0.40	0.999	2.57	0.55	-0.03	1	1.20	0.899	2.11	0.179	0.97	0.949
VP-E	-0.09	1	0.37	0.997	1.26	0.456	1.50	0.468	0.56	0.977	-0.41	0.999	0.63	0.991	1.74	0.87	0.58	0.948	0.47	0.998	0.69	0.973	-0.01	1
G-F	-0.03	1	-0.83	0.945	**-3.33**	**3E-05**	**-3.56**	**3E-04**	-2.05	0.187	-1.82	0.556	**-4.18**	**9E-05**	**-5.78**	**0.002**	0.56	0.958	-0.80	0.98	**-4.98**	**7E-07**	**-6.03**	**7E-07**
P-F	0.98	0.556	1.55	0.285	0.21	1	0.42	0.996	0.46	0.995	0.70	0.988	-0.08	1	-0.95	0.912	0.25	0.999	-0.50	0.984	-0.08	1	-1.17	0.893
VP-F	0.64	0.886	1.18	0.591	0.50	0.979	0.22	1	0.71	0.935	0.07	1	0.15	1	-1.78	0.391	0.86	0.775	-1.23	0.548	-1.50	0.553	-2.15	0.361
P-G	1.00	0.528	**2.38**	**0.025**	**3.53**	**7E-06**	**3.99**	**3E-05**	2.52	0.052	2.52	0.193	**4.10**	**1E-04**	**4.83**	**0.017**	-0.31	0.997	0.29	1	**4.90**	**1E-06**	**4.86**	**1E-04**
VP-G	0.66	0.868	2.02	0.093	**3.83**	**7E-07**	**3.78**	**1E-04**	**2.76**	**0.003**	1.90	0.51	**4.33**	**8E-06**	3.99	0.084	0.31	0.997	-0.44	0.999	**3.48**	**0.002**	**3.88**	**0.005**
VP-P	-0.34	0.993	-0.36	0.985	0.29	0.998	-0.21	1	0.24	1	-0.63	0.993	0.23	0.999	-0.84	0.946	0.61	0.937	-0.73	0.921	-1.42	0.614	-0.98	0.947

Appendix D. TukeyHSD multiple comparisons results between each crop combination by condition for both week 1 and week 2. Table displays the differences between the means along with the corresponding p values. Bolded text represents statistical significance at 0.05 significance level.

	Excellent				Good				Fair				Poor				Very Poor				Crop Condition Index			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
Cot-Cor	-0.37	0.987	-0.84	0.786	-2.19	0.509	-1.47	0.939	1.11	0.833	1.43	0.856	0.35	0.994	0.35	0.994	0.98	0.439	0.86	0.51	-1.37	0.324	-1.36	0.645
Pea-Cor	0.10	1	0.20	1	-1.36	0.916	-0.46	1	0.67	0.984	0.70	0.995	0.16	1	0.16	1	0.31	0.994	-0.01	1	-0.55	0.974	-0.04	1
Ric-Cor	-0.05	1	-1.95	0.394	-2.80	0.676	-2.44	0.924	2.73	0.356	1.42	0.978	-0.10	1	-0.10	1	0.09	1	0.12	1	-0.81	0.967	-3.36	0.157
Sor-Cor	-0.40	0.997	-0.70	0.976	0.63	0.999	2.19	0.933	0.05	1	-0.52	1	-0.68	0.978	-0.68	0.978	0.27	0.999	0.03	1	-0.07	1	0.29	1
Soy-Cor	-0.73	0.844	-0.24	0.999	-2.77	0.324	-2.49	0.704	2.19	0.237	2.89	0.265	1.13	0.556	1.13	0.556	0.05	1	-0.04	1	-1.43	0.367	-0.83	0.957
Pea-Cot	0.47	0.942	1.04	0.482	0.83	0.978	1.01	0.981	-0.44	0.995	-0.73	0.987	-0.19	0.999	-0.19	0.999	-0.67	0.725	-0.87	0.386	0.82	0.752	1.32	0.568
Ric-Cot	0.32	0.999	-1.11	0.85	-0.61	0.999	-0.97	0.998	1.62	0.799	-0.01	1	-0.44	0.996	-0.44	0.996	-0.88	0.834	-0.75	0.909	0.56	0.991	-1.99	0.639
Sor-Cot	-0.03	1	0.14	1	2.82	0.562	3.67	0.508	-1.06	0.956	-1.95	0.844	-1.02	0.836	-1.02	0.836	-0.71	0.922	-0.83	0.81	1.30	0.709	1.66	0.728
Soy-Cot	-0.35	0.983	0.60	0.915	-0.58	0.996	-1.01	0.983	1.08	0.79	1.46	0.796	0.79	0.742	0.79	0.742	-0.93	0.382	-0.91	0.356	-0.05	1	0.54	0.986
Ric-Pea	-0.15	1	-2.15	0.242	-1.44	0.968	-1.98	0.962	2.06	0.624	0.72	0.999	-0.26	1	-0.26	1	-0.21	1	0.12	1	-0.26	1	-3.32	0.135
Sor-Pea	-0.50	0.99	-0.90	0.917	1.99	0.872	2.65	0.834	-0.62	0.997	-1.22	0.981	-0.84	0.935	-0.84	0.935	-0.04	1	0.04	1	0.48	0.996	0.33	1
Soy-Pea	-0.82	0.685	-0.44	0.984	-1.41	0.868	-2.02	0.798	1.52	0.548	2.18	0.49	0.97	0.621	0.97	0.621	-0.26	0.996	-0.04	1	-0.88	0.774	-0.79	0.951
Sor-Ric	-0.35	0.999	1.25	0.894	3.43	0.63	4.63	0.582	-2.68	0.556	-1.94	0.953	-0.58	0.995	-0.58	0.995	0.18	1	-0.09	1	0.74	0.989	3.65	0.203
Soy-Ric	-0.68	0.963	1.71	0.51	0.04	1	-0.04	1	-0.54	0.999	1.47	0.971	1.23	0.754	1.23	0.754	-0.05	1	-0.16	1	-0.61	0.989	2.53	0.42
Soy-Sor	-0.33	0.999	0.46	0.996	-3.40	0.395	-4.68	0.285	2.14	0.564	3.41	0.363	1.81	0.323	1.81	0.323	-0.22	1	-0.07	1	-1.35	0.711	-1.12	0.946

Appendix E. TukeyHSD multiple comparisons results between each condition combination by month for both week 1 and week 2. Table displays the differences between the means along with the corresponding p values. Bolded text represents statistical significance at 0.05 significance level.

	May				**Jun**				**Jul**				**Aug**				**Sep**				**Oct**			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
F-E	-2.60	0.501	-2.47	0.666	-2.07	0.199	**-3.12**	**0.017**	**-3.55**	**1E-06**	**-4.37**	**5E-04**	0.86	0.371	0.42	0.99	**2.22**	**0.028**	**4.02**	**6E-04**	2.96	0.301	**5.58**	**0.021**
G-E	-0.53	0.999	-4.40	0.091	-0.86	0.93	-0.20	1	-1.60	0.146	-1.05	0.917	-1.04	0.175	-1.20	0.502	**-3.60**	**1E-05**	**-4.68**	**3E-05**	-3.00	0.285	-0.91	0.995
P-E	-0.13	1	-1.13	0.983	-0.53	0.992	-0.83	0.955	**-2.02**	**0.027**	-1.79	0.527	-0.18	0.998	-0.48	0.982	**2.06**	**0.053**	**3.73**	**0.002**	**6.24**	**2E-04**	**5.79**	**0.014**
VP-E	-0.07	1	-1.33	0.965	-0.53	0.992	-1.44	0.668	-1.65	0.123	-1.68	0.597	-0.13	1	-0.32	0.997	1.78	0.142	2.36	0.151	3.37	0.171	**4.70**	**0.083**
G-F	2.07	0.731	-1.93	0.847	1.20	0.765	**2.92**	**0.032**	**1.94**	**0.038**	**3.32**	**0.02**	**-1.90**	**3E-04**	-1.61	0.174	**-5.82**	**0**	**-8.70**	**0**	**-5.96**	**5E-04**	**-6.48**	**0.004**
P-F	2.47	0.559	1.33	0.965	1.54	0.526	2.29	0.168	1.53	0.187	2.58	0.137	-1.04	0.169	-0.90	0.778	-0.16	1	-0.29	1	3.28	0.194	0.21	1
VP-F	2.53	0.53	1.13	0.983	1.54	0.526	1.68	0.506	**1.90**	**0.048**	2.69	0.107	-0.99	0.221	-0.73	0.892	-0.44	0.991	-1.66	0.534	0.41	1	-0.88	0.996
P-G	0.40	1	3.27	0.359	0.34	0.999	-0.63	0.987	-0.41	0.989	-0.74	0.981	0.85	0.381	0.71	0.903	**5.66**	**0**	**8.41**	**0**	**9.24**	**0**	**6.70**	**0.002**
VP-G	0.47	1	3.07	0.432	0.34	0.999	-1.24	0.794	-0.05	1	-0.63	0.991	0.91	0.307	0.88	0.794	**5.38**	**0**	**7.04**	**0**	**6.37**	**2E-04**	**5.61**	**0.019**
VP-P	0.07	1	-0.20	1	0.00	1	-0.61	0.988	0.36	0.994	0.11	1	0.06	1	0.16	1	-0.28	0.999	-1.37	0.726	-2.87	0.335	-1.09	0.989

Appendix F. TukeyHSD multiple comparisons results between each month combination by each condition for both week 1 and week 2. Table displays the differences between the means along with the corresponding p values. Bolded text represents statistical significance at 0.05 significance level.

	Excellent				**Good**				**Fair**				**Poor**				**Very Poor**				**Crop Condition Index**			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
May-Jun	-0.13	1	0.75	0.993	0.20	1	-3.45	0.908	-0.66	0.999	1.40	0.994	0.26	1	0.45	1	0.33	1	0.86	0.962	-0.24	1	-1.03	0.996
May-Jul	-1.09	0.933	0.09	1	0.54	1	-3.26	0.917	-0.96	0.996	1.99	0.965	1.03	0.964	0.75	0.997	0.48	0.998	0.43	0.998	-0.90	0.984	-1.17	0.991
May-Aug	0.77	0.981	1.59	0.784	1.12	0.998	-1.17	0.999	-3.13	0.511	-1.30	0.994	0.53	0.998	0.94	0.99	0.64	0.99	0.57	0.992	0.18	1	0.30	1
Jun-Jul	-0.96	0.743	-0.66	0.957	0.34	1	0.19	1	-0.30	1	0.59	0.999	0.77	0.917	0.30	1	0.15	1	-0.42	0.983	-0.66	0.965	-0.15	1
Jun-Aug	0.90	0.692	0.84	0.827	0.92	0.986	2.28	0.79	-2.47	0.151	-2.70	0.331	0.26	0.999	0.49	0.993	0.32	0.995	-0.28	0.995	0.43	0.992	1.33	0.808
Jul-Aug	**1.86**	**0.011**	1.50	0.147	0.58	0.997	2.10	0.772	-2.17	0.166	-3.29	0.067	-0.50	0.963	0.19	1	0.17	1	0.14	1	1.08	0.549	1.47	0.625
Sep-May	-1.16	0.897	-3.08	0.119	-4.23	0.518	-3.36	0.892	3.66	0.323	3.41	0.699	1.04	0.955	1.79	0.849	0.69	0.986	0.62	0.988	-2.24	0.496	-3.44	0.438
Sep-Jun	-1.29	0.286	**-2.33**	**0.01**	**-4.02**	**0.041**	**-6.80**	**0.002**	**3.00**	**0.035**	**4.81**	**0.004**	1.30	0.382	2.23	0.098	1.02	0.5	**1.48**	**0.073**	**-2.48**	**0.007**	**-4.47**	**4E-04**
Sep-Jul	**-2.25**	**7E-04**	**-2.99**	**2E-05**	**-3.68**	**0.033**	**-6.62**	**4E-04**	**2.71**	**0.033**	**5.40**	**1E-04**	**2.06**	**0.008**	**2.53**	**0.013**	1.16	0.219	1.05	0.252	**-3.14**	**2E-05**	**-4.62**	**2E-05**
Sep-Aug	-0.39	0.954	**-1.49**	**0.039**	**-3.10**	**0.024**	**-4.52**	**0.007**	0.53	0.978	2.11	0.256	**1.56**	**0.018**	**2.72**	**3E-04**	**1.33**	**0.021**	**1.19**	**0.034**	**-2.06**	**0.001**	**-3.14**	**8E-04**
Sep-Oct	1.42	0.288	**1.82**	**0.281**	**0.82**	**0.994**	**-1.95**	**0.951**	0.69	0.99	0.26	1	**-2.76**	**0.003**	**-0.24**	**1**	**-0.17**	**1**	**-0.51**	**0.975**	**1.69**	**0.265**	**0.43**	**0.999**
Oct-May	-2.58	0.273	**-4.90**	**0.007**	-5.05	0.427	-1.41	0.999	2.98	0.666	3.15	0.858	**3.79**	**0.049**	2.02	0.859	0.86	0.976	1.13	0.911	-3.93	0.061	-3.87	0.467
Oct-Jun	**-2.71**	**0.01**	**-4.15**	**4E-04**	-4.85	0.076	-4.85	0.387	2.31	0.492	4.55	0.161	**4.05**	**7E-05**	2.47	0.337	1.19	0.623	1.99	0.108	**-4.17**	**1E-04**	**-4.90**	**0.015**
Oct-Jul	**-3.67**	**2E-05**	**-4.81**	**5E-06**	-4.51	0.082	-4.67	0.373	2.02	0.575	5.14	0.052	**4.82**	**1E-07**	2.77	0.167	1.33	0.42	1.57	0.274	**-4.83**	**8E-07**	**-5.05**	**0.006**
Oct-Aug	**-1.81**	**0.087**	**-3.31**	**0.002**	-3.93	0.106	-2.57	0.856	-0.15	1	1.85	0.879	**4.32**	**2E-07**	2.96	0.07	1.50	0.186	1.70	0.127	**-3.75**	**5E-05**	-3.57	0.077

Appendix G. TukeyHSD multiple comparisons results between each condition combination by tropical cyclone intensity for both week 1 and week 2. Table displays the differences between the means along with the corresponding p values. Bolded text represents statistical significance at 0.05 significance level.

	TD				TS				H1				H2				H3				H4			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
F-E	-0.3	0.992	-1.0	0.544	-0.3	0.981	-0.3	0.992	**3.6**	**0.02**	4.6	0.137	4.5	0.111	5.2	0.051	1.2	0.995	0.2	1	6.6	0.804	12.8	0.362
G-E	-0.7	0.703	-0.9	0.691	-0.8	0.484	-1.3	0.253	**-4.9**	**4E-04**	**-6.3**	**0.011**	**-5.7**	**0.017**	**-5.4**	**0.037**	**-10.5**	**3E-04**	-6.5	0.207	-11.1	0.283	-13.5	0.304
P-E	-0.6	0.886	-1.2	0.423	0.2	0.997	0.2	1	**5.1**	**2E-04**	**5.9**	**0.022**	3.9	0.233	**5.2**	**0.047**	2.3	0.929	6.6	0.201	6.3	0.831	6.7	0.903
VP-E	-0.6	0.808	-1.0	0.544	0.3	0.99	-0.1	1	2.5	0.253	3.4	0.465	3.1	0.519	3.6	0.341	1.5	0.99	3.9	0.745	7.9	0.658	6.3	0.923
G-F	-0.4	0.957	0.1	1	-0.5	0.896	-0.9	0.605	**-8.5**	**0**	**-10.9**	**2E-07**	**-10.3**	**2E-07**	**-10.5**	**2E-07**	**-11.7**	**4E-05**	-6.8	0.175	**-17.6**	**0.013**	**-26.2**	**0.002**
P-F	-0.3	0.996	-0.1	1	0.5	0.846	0.5	0.948	1.5	0.792	1.3	0.984	-0.6	0.999	0.1	1	1.0	0.998	6.3	0.236	-0.3	1	-6.1	0.934
VP-F	-0.3	0.985	0.0	1	0.6	0.773	0.2	0.999	-1.2	0.916	-1.2	0.986	-1.5	0.961	-1.5	0.958	0.2	1	3.7	0.792	1.3	1	-6.5	0.915
P-G	0.2	0.999	-0.3	0.999	1.0	0.218	1.5	0.13	**10.0**	**0**	**12.2**	**0**	**9.7**	**1E-06**	**10.6**	**2E-07**	**12.7**	**5E-06**	**13.1**	**2E-04**	**17.4**	**0.016**	**20.2**	**0.029**
VP-G	0.1	1	-0.1	1	1.0	0.162	1.1	0.376	**7.4**	**0**	**9.7**	**6E-06**	**8.8**	**2E-05**	**9.0**	**2E-05**	**11.9**	**2E-05**	**10.4**	**0.005**	**18.9**	**0.006**	**19.8**	**0.034**
VP-P	-0.1	1	0.1	1	0.1	1	-0.3	0.994	-2.6	0.199	-2.5	0.759	-0.9	0.996	-1.6	0.951	-0.8	0.999	-2.7	0.937	1.6	1	-0.4	1

Appendix H. TukeyHSD multiple comparisons results between each tropical cyclone type by condition for both week 1 and week 2. Table displays the differences between the means along with the corresponding p values. Bolded text represents statistical significance at 0.05 significance level.

	Excellent				**Good**				**Fair**				**Poor**				**Very Poor**				**Crop Condition Index**			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
TD-H1	**1.7**	**0.04**	**2.7**	**0.002**	**5.9**	**6E-05**	**8.1**	**5E-05**	-2.2	0.195	-3.0	0.231	**-3.9**	**0**	**-4.4**	**5E-06**	-1.4	0.1	**-1.7**	**0.016**	**4.0**	**0**	**6.2**	**1E-07**
TD-H2	1.1	0.747	**2.7**	**0.047**	**5.1**	**0.049**	5.7	0.139	-3.3	0.143	-3.8	0.278	-0.8	0.944	-2.5	0.225	-2.0	0.079	**-2.1**	**0.042**	**3.1**	**0.013**	**4.4**	**0.018**
TD-H3	-0.6	0.983	**1.7**	**0.603**	**9.1**	**7E-05**	7.3	0.061	-2.2	0.704	0.4	1	**-3.5**	**0.007**	**-6.0**	**4E-05**	**-2.7**	**0.016**	**-3.3**	**8E-04**	**4.2**	**9E-04**	**5.8**	**0.003**
TD-H4	2.4	0.288	**3.3**	**0.126**	**12.7**	**3E-06**	**15.8**	**2E-05**	-4.5	0.149	**-10.5**	**5E-04**	**-4.5**	**0.004**	**-4.6**	**0.048**	**-6.1**	**1E-07**	**-4.1**	**8E-04**	**8.6**	**0**	**8.8**	**1E-04**
TS-H1	1.4	0.152	**2.1**	**0.026**	**5.5**	**1E-04**	**7.1**	**4E-04**	-2.6	0.075	-2.9	0.238	**-3.5**	**4E-07**	**-3.6**	**2E-04**	-0.8	0.607	-1.4	0.069	**3.4**	**4E-06**	**5.1**	**9E-06**
TS-H2	0.8	0.927	2.1	0.212	4.7	0.078	4.7	0.312	-3.6	0.072	-3.7	0.29	-0.4	0.998	-1.8	0.6	-1.5	0.36	-1.8	0.118	**2.4**	**0.093**	3.3	0.147
TS-H3	-1.0	0.895	1.1	0.907	**8.7**	**1E-04**	6.3	0.146	-2.5	0.548	0.5	1	**-3.0**	**0.026**	**-5.3**	**4E-04**	-2.2	0.101	**-3.0**	**0.003**	**3.5**	**0.009**	**4.6**	**0.033**
TS-H4	2.0	0.456	2.7	0.314	**12.4**	**6E-06**	**14.9**	**8E-05**	-4.8	0.093	**-10.4**	**5E-04**	**-4.0**	**0.012**	-3.8	0.149	**-5.6**	**2E-06**	**-3.8**	**0.002**	**7.9**	**0**	**7.7**	**0.001**
TS-TD	-0.3	0.963	-0.6	0.786	-0.4	0.999	-1.0	0.957	-0.3	0.996	0.1	1	0.4	0.935	0.7	0.781	0.6	0.662	0.3	0.958	-0.7	0.691	-1.1	0.588
H2-H1	0.6	0.987	0.0	1	0.8	0.999	2.4	0.94	1.1	0.979	0.8	0.999	**-3.1**	**0.022**	-1.9	0.691	0.6	0.974	0.3	0.998	1.0	0.94	1.8	0.864
H3-H1	2.4	0.177	1.0	0.953	-3.2	0.671	0.8	1	-0.1	1	-3.4	0.659	-0.5	0.998	1.7	0.84	1.3	0.701	1.5	0.512	-0.1	1	0.4	1
H3-H2	1.8	0.652	1.0	0.974	-4.0	0.592	-1.6	0.996	-1.1	0.991	-4.2	0.561	2.6	0.284	3.5	0.23	0.7	0.987	1.2	0.844	-1.1	0.963	-1.3	0.984
H4-H1	-0.7	0.994	-0.6	0.998	-6.8	0.085	-7.7	0.23	2.3	0.857	7.6	0.058	0.5	0.999	0.2	1	**4.7**	**3E-04**	2.3	0.247	**-4.5**	**0.012**	-2.6	0.819
H4-H2	-1.3	0.938	-0.6	0.999	-7.6	0.082	-10.2	0.083	1.2	0.994	6.7	0.2	3.6	0.119	2.1	0.878	4.1	0.012	2.0	0.531	**-5.5**	**0.004**	-4.4	0.393
H4-H3	-3.0	0.258	-1.6	0.92	-3.6	0.828	-8.5	0.272	2.3	0.911	10.9	0.006	1.0	0.986	-1.5	0.974	3.4	0.088	0.8	0.987	-4.4	0.058	-3.0	0.806

Appendix I. TukeyHSD multiple comparisons results between each condition combination by precursor soil moisture and growing season timing for both week 1 and week 2. Table displays the differences between the means along with the corresponding p values. Bolded text represents statistical significance at 0.05 significance level.

	Wet- early				**Wet- mid**				**Wet- late**			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
F-E	-0.6	0.997	-2.1	0.839	-0.5	0.997	**-4.0**	**0.023**	0.7	0.952	**6.2**	**0.033**
G-E	-1.1	0.942	-1.8	0.915	-2.7	0.145	-3.1	0.147	-1.3	0.459	-3.2	0.628
P-E	-0.1	1	-1.3	0.974	-0.4	1	-1.4	0.878	1.2	0.574	3.7	0.458
VP-E	1.8	0.694	-0.3	1	-0.6	0.995	-1.8	0.72	1.1	0.67	2.8	0.736
G-F	-0.6	0.997	0.3	1	-2.2	0.359	0.9	0.983	-2.0	0.081	**-9.3**	**1E-04**
P-F	0.4	0.999	0.8	0.998	0.2	1	2.6	0.324	0.6	0.974	-2.5	0.836
VP-F	2.3	0.41	1.8	0.915	-0.1	1	2.2	0.511	0.5	0.99	-3.3	0.579
P-G	1.0	0.963	0.4	1	2.4	0.281	1.7	0.765	**2.6**	**0.008**	**6.9**	**0.011**
VP-G	2.9	0.19	1.4	0.963	2.1	0.396	1.3	0.906	**2.5**	**0.014**	**6.0**	**0.041**
VP-P	1.9	0.638	1.0	0.993	-0.2	1	-0.4	1	-0.1	1	-0.9	0.998
	Dry- early				**Dry- mid**				**Dry- late**			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
F-E	-2.7	0.875	-8.9	0.133	0.6	0.997	-0.5	1	0.7	0.976	2.5	0.507
G-E	2.2	0.938	-0.9	1	0.9	0.983	1.2	0.986	-0.7	0.976	-3.3	0.193
P-E	0.1	1	0.7	1	-0.5	0.999	-1.9	0.913	1.9	0.319	2.6	0.463
VP-E	-0.2	1	-4.8	0.748	-1.4	0.912	-1.6	0.958	0.7	0.97	0.6	0.999
G-F	4.9	0.338	8.0	0.221	0.3	1	1.8	0.936	-1.4	0.666	**-5.7**	**9E-04**
P-F	2.8	0.855	9.6	0.088	-1.1	0.96	-1.4	0.977	1.2	0.787	0.1	1
VP-F	2.4	0.91	4.1	0.847	-2.0	0.68	-1.1	0.993	0.0	1	-1.9	0.76
P-G	-2.1	0.95	1.6	0.998	-1.4	0.893	-3.1	0.549	2.6	0.061	**5.8**	**7E-04**
VP-G	-2.4	0.91	-3.9	0.875	-2.3	0.531	-2.8	0.658	1.4	0.643	3.8	0.077
VP-P	-0.3	1	-5.4	0.632	-0.9	0.988	0.3	1	-1.2	0.807	-2.0	0.719
	Near Normal- early				**Near Normal- mid**				**Near Normal- late**			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
F-E	-2.4	0.119	-2.2	0.164	-0.1	1	-0.6	0.958	**3.4**	**0.001**	**4.5**	**0.004**
G-E	-1.2	0.773	-1.0	0.898	-1.3	0.147	-1.0	0.654	**-4.7**	**6E-07**	**-4.8**	**0.002**
P-E	-0.6	0.989	-1.1	0.849	-0.8	0.693	-0.6	0.944	**2.7**	**0.017**	**5.0**	**9E-04**
VP-E	-0.8	0.951	-1.1	0.858	-0.3	0.99	-0.4	0.995	2.0	0.135	**3.8**	**0.025**
G-F	1.1	0.834	1.2	0.768	-1.3	0.183	-0.5	0.986	**-8.1**	**0**	**-9.2**	**0**
P-F	1.8	0.407	1.1	0.83	-0.7	0.753	0.0	1	-0.7	0.961	0.5	0.998
VP-F	1.5	0.568	1.1	0.821	-0.3	0.996	0.2	1	-1.3	0.599	-0.6	0.995
P-G	0.6	0.983	-0.1	1	0.5	0.926	0.4	0.991	**7.4**	**0**	**9.8**	**0**
VP-G	0.4	0.998	-0.1	1	1.0	0.455	0.7	0.924	**6.8**	**0**	**8.6**	**0**
VP-P	-0.2	1	0.0	1	0.5	0.959	0.3	0.999	-0.6	0.972	-1.2	0.938

Appendix J. TukeyHSD multiple comparisons results between each precursor soil moisture and timing classification combination by condition for both week 1 and week 2. Table displays the differences between the means along with the corresponding p values. Bolded text represents statistical significance at 0.05 significance level.

	Excellent				**Good**				**Fair**				**Poor**				**Very Poor**				**Crop Condition Index**			
	Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2		Week 1		Week 2	
	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val	Diff	p-val
Dry-Late-Dry-Early	-0.6	1	-3.2	0.558	-3.5	0.973	-5.6	0.901	2.7	0.968	8.1	0.208	1.1	0.999	-1.3	0.999	0.3	1	2.1	0.775	-1.6	0.988	-3.7	0.752
Dry-Mid-Dry-Early	0.0	1	-2.2	0.935	-1.3	1	-0.1	1	3.2	0.939	6.1	0.66	-0.7	1	-4.8	0.384	-1.2	0.996	1.0	0.998	0.4	1	-0.4	1
Dry-Mid-Dry-Late	0.6	0.999	1.0	0.989	2.2	0.976	5.5	0.454	0.5	1	-2.0	0.989	-1.8	0.698	-3.4	0.171	-1.5	0.712	-1.1	0.902	2.0	0.589	3.3	0.322
NN-Early-Dry-Early	0.9	1	-1.7	0.98	-2.6	0.997	-1.8	1	1.2	1	5.0	0.816	0.2	1	-3.5	0.736	0.3	1	2.0	0.812	-0.4	1	-1.4	0.999
NN-Late-Dry-Late	-0.6	0.992	-1.2	0.799	**-5.7**	**0.002**	-2.7	0.881	2.7	0.23	0.8	1	1.7	0.281	1.2	0.947	**1.9**	**0.041**	2.0	0.021	**-3.1**	**0.001**	-2.6	0.226
NN-Late-NN-Early	**-2.1**	**0.045**	**-2.8**	**0.008**	**-6.7**	**2E-04**	**-6.6**	**0.013**	**4.2**	**0.004**	3.9	0.16	**2.7**	**0.009**	**3.3**	**0.013**	**2.0**	**0.046**	**2.1**	**0.009**	**-4.4**	**6E-07**	**-4.9**	**6E-05**
NN-Mid-Dry-Mid	0.4	1	0.0	1	-1.8	0.985	-2.3	0.983	-0.2	1	-0.1	1	0.2	1	1.2	0.974	1.5	0.582	1.2	0.756	-1.0	0.981	-1.5	0.953
NN-Mid-NN-Early	-0.5	0.998	-0.5	0.998	-0.6	1	-0.6	1	1.8	0.708	1.1	0.997	-0.7	0.986	-0.1	1	0.0	1	0.2	1	-0.2	1	-0.5	1
NN-Mid-NN-Late	**1.6**	**0.032**	**2.2**	**0.003**	**6.1**	**1E-06**	**6.0**	**8E-04**	-2.4	0.084	-2.8	0.2	**-3.4**	**1E-07**	**-3.4**	**7E-05**	**-2.0**	**1E-03**	**-2.0**	**3E-04**	**4.2**	**0**	**4.4**	**4E-07**
Wet-Early-Dry-Early	-0.1	1	-1.7	0.997	-3.4	0.996	-2.6	1	2.0	0.999	5.1	0.949	-0.3	1	-3.7	0.903	1.9	0.98	2.8	0.76	-1.8	0.997	-1.9	0.999
Wet-Early-NN-Early	-1.0	0.999	0.1	1	-0.9	1	-0.8	1	0.8	1	0.1	1	-0.5	1	-0.2	1	1.6	0.962	0.8	1	-1.4	0.996	-0.5	1
Wet-Late-Dry-Late	0.2	1	-1.9	0.521	-0.5	1	-1.8	0.997	0.2	1	1.8	0.99	-0.5	1	-0.8	0.999	0.6	0.997	0.3	1	-0.2	1	-2.6	0.504
Wet-Late-NN-Late	0.8	0.974	-0.7	0.996	**5.2**	**0.024**	0.9	1	-2.5	0.437	1.0	1	-2.2	0.122	-2.0	0.618	-1.3	0.524	-1.7	0.188	**2.9**	**0.011**	0.0	1
Wet-Late-Wet-Early	-0.3	1	-3.5	0.475	-0.6	1	-4.9	0.959	0.9	1	4.8	0.871	1.0	1	1.5	0.998	-1.0	0.999	-0.4	1	-0.1	1	-4.4	0.568
Wet-Mid-Dry-Mid	0.8	0.997	1.4	0.939	-2.9	0.916	-3.0	0.973	-0.4	1	-2.1	0.986	0.9	0.995	1.9	0.901	1.6	0.738	1.2	0.9	-1.3	0.955	-1.0	0.999
Wet-Mid-NN-Mid	0.3	1	1.4	0.661	-1.1	0.999	-0.7	1	-0.1	1	-2.0	0.916	0.8	0.986	0.6	0.999	0.1	1	0.0	1	-0.4	1	0.5	1
Wet-Mid-Wet-Early	0.8	1	0.8	1	-0.8	1	-0.5	1	0.9	1	-1.1	1	0.6	1	0.7	1	-1.5	0.975	-0.6	1	0.8	1	0.5	1
Wet-Mid-Wet-Late	1.2	0.919	**4.3**	**5E-04**	-0.2	1	4.4	0.692	0.0	1	-5.8	0.064	-0.4	1	-0.8	0.999	-0.5	0.999	-0.3	1	0.9	0.992	**5.0**	**0.008**

Appendix K. Regression equations from Fig. 7 for each crop and state.

	Corn	Cotton	Peanuts	Rice	Sorghum	Soybeans
Texas	$Yield_{Est}$ = 46.679(X) + 6052	N/A	$Yield_{Est}$ = 30.166(X) + 2302	N/A	$Yield_{Est}$ = 31.407(X) + 2040	$Yield_{Est}$ = 41.017(X) - 241.38
Louisiana	$Yield_{Est}$ = 77.071(X) + 7223	$Yield_{Est}$ = 13.794(X) + 263	$Yield_{Est}$ = 6.4803(X) + 4302	$Yield_{Est}$ = 36.47(X) + 5476	$Yield_{Est}$ = 47.884(X) + 3624	$Yield_{Est}$ = 28.26(X) + 1759
Mississippi	N/A	$Yield_{Est}$ = 8.2863(X) + 713	N/A	$Yield_{Est}$ = 17.8(X) + 7115	$Yield_{Est}$ = 25.825(X) + 4160	$Yield_{Est}$ = 12.397(X) + 2775
Alabama	$Yield_{Est}$ = 77.364(X) + 5364	$Yield_{Est}$ = 7.1162(X) + 566	$Yield_{Est}$ = 22.794(X) + 2559	N/A	N/A	$Yield_{Est}$ = 18.875(X) + 1622
Florida	N/A	N/A	$Yield_{Est}$ = 22.28(X) + 2724	N/A	N/A	N/A
Georgia	$Yield_{Est}$ = 48.784(X) + 9326	$Yield_{Est}$ = 8.6785(X) + 516	$Yield_{Est}$ = 36.135(X) + 2530	N/A	N/A	$Yield_{Est}$ = 23.428(X) + 1273
South Carolina	$Yield_{Est}$ = 122.05(X) + 407	$Yield_{Est}$ = 8.6415(X) + 442	N/A	N/A	N/A	$Yield_{Est}$ = 17.05(X) + 1137
North Carolina	$Yield_{Est}$ = 93.772(X) + 2975	$Yield_{Est}$ = 15.017(X) + 74	$Yield_{Est}$ = 61.132(X) + 312	N/A	N/A	$Yield_{Est}$ = 31.743(X) + 459

Appendix L. TukeyHSD multiple comparisons results for both yield changes after the tropical cyclone and yield changes at the end of the growing season by crop, month, intensity, and precursor soil moisture classification. Table displays the differences between the means along with the corresponding p values. Bolded text represents statistical significance at 0.05 significance level.

Crop					**Month**					**Intensity**				
	TC Impact		End of Year			TC Impact		End of Year			TC Impact		End of Year	
Crop	Diff	p-val	Diff	p-val	Month	Diff	p-val	Diff	p-val	Intensity	Diff	p-val	Diff	p-val
Cot-Cor	-0.7	0.958	0.1	1	May-Jun	-0.2	1	0.2	1	TD-H1	**4.0**	**3E-05**	3.4	0.178
Pea-Cor	0.0	1	-0.5	0.999	May-Jul	-1.3	0.971	-0.7	1	TD-H2	**3.5**	**0.028**	2.4	0.858
Ric-Cor	1.1	0.977	-0.4	1	May-Aug	-1.4	0.951	-3.2	0.854	TD-H3	2.7	0.296	4.1	0.443
Sor-Cor	0.4	1	-0.5	1	Jun-Jul	-1.0	0.915	-0.9	0.995	TD-H4	**7.6**	**6E-05**	4.7	0.601
Soy-Cor	0.4	0.998	1.3	0.929	Jun-Aug	-1.1	0.815	-3.4	0.272	TS-TD	-1.3	0.188	-2.1	0.272
Pea-Cot	0.7	0.938	-0.6	0.997	Jul-Aug	-0.1	1	-2.4	0.495	TS-H1	**2.7**	**0.015**	1.3	0.948
Ric-Cot	1.8	0.833	-0.5	1	Sep-May	-1.2	0.97	-0.4	1	TS-H2	2.2	0.386	0.2	1
Sor-Cot	1.0	0.926	-0.6	0.999	Sep-Jun	-1.5	0.581	-0.2	1	TS-H3	1.4	0.887	1.9	0.953
Soy-Cot	1.0	0.717	1.2	0.929	Sep-Jul	**-2.5**	**0.019**	-1.2	0.957	TS-H4	**6.3**	**0.002**	2.5	0.955
Ric-Pea	1.1	0.978	0.1	1	Sep-Aug	**-2.6**	**8E-04**	**-3.6**	**0.016**	H2-H1	0.5	0.999	1.1	0.997
Sor-Pea	0.3	1	0.0	1	Sep-Oct	0.4	0.997	-0.2	1	H3-H1	1.2	0.952	-0.6	1
Soy-Pea	0.3	0.998	1.8	0.727	Oct-May	-1.7	0.927	-0.2	1	H3-H2	0.8	0.997	-1.7	0.991
Sor-Ric	-0.8	0.997	-0.1	1	Oct-Jun	-1.9	0.572	0.0	1	H4-H1	-3.6	0.287	-1.2	0.999
Soy-Ric	-0.8	0.995	1.7	0.986	Oct-Jul	-2.9	0.072	-1.0	0.996	H4-H2	-4.1	0.262	-2.3	0.985
Soy-Sor	0.0	1	1.8	0.918	Oct-Aug	**-3.0**	**0.024**	-3.4	0.348	H4-H3	-4.9	0.144	-0.6	1

Wet Soil					**Near Normal Soil**					**Dry Soil**				
	TC Impact		End of Year			TC Impact		End of Year			TC Impact		End of Year	
Timing	Diff	p-val	Diff	p-val	Timing	Diff	p-val	Diff	p-val	Timing	Diff	p-val	Diff	p-val
Late-Early	0.4	0.982	4.1	0.434	Late-Early	-1.7	0.189	-1.7	0.474	Late-Early	-3.0	0.27	-1.1	0.97
Mid-Early	2.5	0.549	2.4	0.754	Mid-Early	1.4	0.299	2.5	0.153	Mid-Early	-1.1	0.85	5.3	0.59
Mid-Late	2.1	0.219	-1.7	0.572	Mid-Late	3.1	**9E-05**	4.2	**3E-04**	Mid-Late	1.9	0.29	6.4	0.11

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