Use of Real-Time Multisensor Data to Assess the Relationship of Normalized Corn Yield with Monthly Rainfall and Heat Stress across the Central United States

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ABSTRACT

This study evaluated the suitability of rain estimates based on the National Weather Service (NWS) Weather Surveillance Radar-1988 Doppler (WSR-88D) network to estimate yield response to rainfall on a county scale and to provide real-time information related to crop stress resulting from deficient or excessive precipitation throughout the summer. The relationship between normalized corn yield and rainfall was examined for nine states in the central United States for 1997–99 and 2001–02. Monthly rainfall estimates were computed employing multisensor precipitation estimate (MPE) data from the National Centers for Environmental Prediction and quality-controlled (QC_Coop) and real-time (RT_Coop) NWS cooperative gauge data. In-season MPE rain estimates were found to be of comparable quality to the postseason QC_Coop estimates for predicting county corn yields. Both MPE and QC_Coop estimates were better related to corn yield than were RT_Coop estimates, presumably because of the lower density of RT_Coop gauges. Large corn yields typically resulted when May rain was less than 125 mm and July rain was greater than 50 mm. Low yields often occurred when July rainfall was less than 100 mm. For moderate July rains (50–100 mm), positive and negative normalized yields resulted. Parameterization of heat stress (number of July days $> 32.2°C$) improved the correlation between rainfall and normalized corn yield, particularly for years with the poorest yield-vs-rain relationship (1998 and 1999). For the combined analysis years, the multiple regression correlation coefficient was 0.56, incorporating May and July rainfall and July heat stress and explaining 31% of the variance of normalized corn yield. Results show that MPE rainfall estimates provide timely yield projections within the growing season.

1. Introduction

In the central United States, rainfall is a major factor in determining corn (*Zea mays* L.) yield. Using regression analysis, Thompson (1986) found that the highest corn yields were associated with normal preseason precipitation and above-normal July and August rainfall. Adequate rainfall in July is important, because that is when grain yield is strongly affected by the success of kernel pollination. During this same period, high temperatures can adversely affect pollination (Herrero and Johnson 1980) and result in low kernel weight and yield loss (Thompson 1975).

Although the current supply and demand of corn worldwide largely determine corn prices, corn prices also depend on estimates of future production. Throughout the growing season considerable effort is expended in projecting the final corn yield, because corn producers and processors attempt to sell or purchase corn at prices that are favorable to their operations. Yield is related to growing-season rainfall. Therefore, both producers and processors monitor the timing and spatial distribution of rainfall throughout the corn-growing regions of the central United States.

Studies relating rainfall, heat stress, and crop yield over large areas, such as the Midwest, are typically based on state or climatic division data (e.g., Bauer and Randall 1982; Carlson 1990; Chen et al. 2004). Summer rainfall in the central United States, however, is highly variable in space because of its convective nature. The variability in rainfall results in high spatial variability in soil moisture, crop stress, and crop yield. Monitoring rainfall conditions and identifying areas of potential crop damage resulting from deficient or excessive rainfall can be problematic because the existing network of precipitation observations is not of sufficient spatial resolution to identify many substantial small-scale

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variations in precipitation. Further, a 2–3-month delay in the availability of quality-controlled cooperative rainfall data prevents timely monitoring of precipitation.

With the establishment of the National Weather Service (NWS) Weather Surveillance Radar-1988 Doppler (WSR-88D) radar network in the mid-1990s, real-time estimates of rainfall became available on a daily basis at a 4-km resolution. These high-resolution data provide an opportunity to evaluate the variability of yield responses to rainfall on a county scale over hundreds of counties and provide important information about areas of deficient or excessive precipitation in real time throughout the summer months.

The principal objective of this study is to assess whether high-resolution radar data can improve real-time corn yield estimates. This assessment will be made by examining the relationship of rainfall estimates from high-resolution gridded multisensor data obtained in near–real time from the National Centers for Environmental Prediction (NCEP) and estimates from the NWS cooperative gauges from the National Climatic Data Center (NCDC) with county-level normalized corn yields for a nine-state region (Fig. 1). Rainfall during the planting period and during the tassel and pollination period of corn growth is examined. Because high temperatures can have a negative impact corn yield, an estimate of heat stress is included in the analysis.

2. Data and analysis

Rainfall data were collected from three sources for this study: 1) hourly gridded precipitation estimates based upon the WSR-88D radars and hourly rain gauge data, 2) daily quality-controlled NWS cooperative rain gauge (QC_Coop) data from NCDC, and 3) daily real-time NWS cooperative rain gauge (RT_Coop) data captured by the Midwestern Regional Climate Center (MRCC). The QC_Coop data are considered as the reference standard for the two real-time precipitation datasets.

The real-time and quality-controlled data differ primarily in the number of reporting gauges. Relative to the number of gauges that report consistently in real time, there are approximately 2 times as many gauges available in the quality-controlled dataset. It has been the past practice at the MRCC that the preliminary RT_Coop data are overwritten by the QC_Coop data upon their availability. Archiving RT_Coop data only began at the Illinois State Water Survey in 2001 for this analysis. The overall analysis period, however, covers the summers of 1997–99 and 2001–02. The gridded precipitation estimates were not available during much of the spring and summer of 2000.

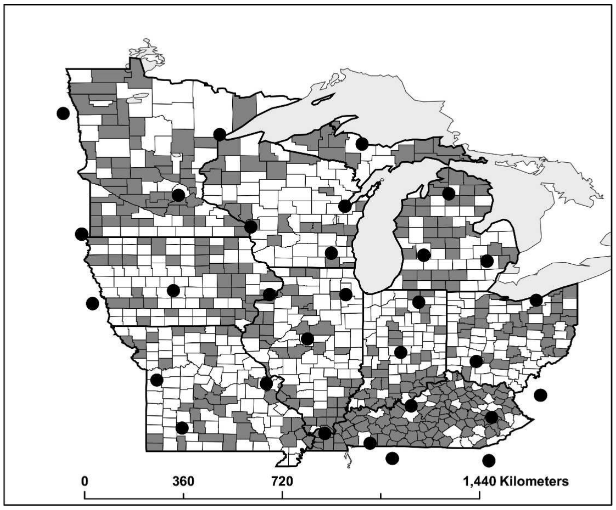

FIG. 1. Counties in the nine-state study region. Shaded counties indicate absence of RT_Coop data during at least one of the May or Jul months in 2001 or 2002. Circles indicate location of the Next-Generation Weather Radars (NEXRAD).

a. Gridded precipitation fields

Gridded (15 or 4 km) hourly multisensor precipitation estimates have been obtained in near–real time from NCEP since March of 1997. These estimates are based upon a composite of data from the WSR-88D radars and upon hourly rain gauge observations from the Hydrometeorological Automated Data System (HADS). The gridded data are downloaded on a daily basis and summed over the 24-h period (valid at 0600 central standard time). County averages are computed for the radar, gauge, and multisensor precipitation estimates (MPE) for the central United States and are stored for analysis. On average, there are seven grid points per county.

Multisensor rainfall estimates are a combination of real-time NWS radar estimates and hourly rainfall measurements. Within the analysis region, approximately 30 radars (Fig. 1) and about 800 hourly gauges are employed in computing the multisensor estimates. No real-time quality control is incorporated into the gridded gauge analysis. The gridded multisensor field was developed to account for spatial inhomogeneities in the rainfall estimates, under the assumption that the radar mean bias error has been removed (Fulton et al. 1998). A local adjustment is made to the rainfall estimates using a multivariate optimal estimation procedure that incorporates point gauge data into the rainfall analysis. The weights for radar and gauge estimates at each grid point are determined so that their linear combination minimizes the expected error variance of the estimate. A decreasing weight is placed on the gauge as the distance increases from the gauge, and an increasing weight is placed on the radar estimate (Fulton et al. 1998; Seo 1998). This technique, detailed by Seo (1998), attempts to account for within-storm variability of rainfall and for variability resulting from the fractional coverage of rainfall (i.e., one instrument reports rainfall where the other does not).

b. *Cooperative rain gauge estimates*

The QC_Coop daily precipitation data, available some 3 months after the fact, were obtained from NCDC. These data are double keyed to minimize input errors and, for warm-season precipitation, the precipitation amounts are checked against a table of monthly extreme values. The quality-control procedures are detailed in Reek et al. (1992). The gauges employed are usually standard 8-in. (20 cm) nonrecording gauges or Automated Surface Observing System gauges. Only gauges having 90% or more data reported during the period were used. There were approximately 1500 cooperative gauges meeting this criterion during this period, with 775 of the 858 counties in the study region containing at least one quality-controlled rain gauge. This resulted in an average of about two gauges per county in counties with gauges, or about one gauge per 800 square kilometers. Reporting times of the cooperative gauges vary, with some at midnight, many between 0500 and 900 LST, and a few at other times of the day. Observation times reported by the cooperative observers can vary from day to day. All gauges, regardless of observation time, were employed in computing the QC_Coop monthly county averages. About 15% of the QC_Coop gauges were part of the real-time HADS hourly gauge dataset.

During the summers of 2001 and 2002 the original real-time data were archived daily. About 725 RT_Coop gauges were employed in this analysis, with about 66% reporting between 0500 and 0900 LST, 19% between 2200 and 0400 LST, and 15% at other times. Figure 1 indicates the number of counties that contain at least one real-time gauge that reported in May and July of 2001 and 2002. Only about 530 of the 858 counties (61%) had at least one rain gauge reporting during the summers of 2001 and 2002, with an average of about 1.3 gauges per county or about 1 gauge per 1250 square kilometers. About 15% of the RT_Coop gauges were part of the real-time HADS hourly gauge dataset.

c. *Heat stress and crop yield*

In addition to rainfall amounts, heat stress also may be important in determining corn yield (Runge 1968). Temperature data were extracted from the QC_Coop data for use in estimating heat stress, defined as the number of days with temperatures equaling or exceeding 32.2°C during July for each county. In general, temperatures above 32°C are considered to be detrimental to corn yield, with the magnitude of yield reduction related to the duration of high temperatures and the severity of drought stress (Thompson 1975; Herrero and Johnson 1980).

County corn yields were obtained from the U.S. Department of Agriculture National Agricultural Statistics Service (available online at the time of writing at http://www.usda.gov/nass/pubs/histdata.htm). The county yield was normalized for each county for each year by subtracting the preceding 5-yr average yield for that county from the county yield. Thus, the deviation from average was computed for each county. This method was used because some areas in the nine-state region average more than 9 Mg ha^{-1} [140 bushels per acre (bu ac^{-1}); southern Minnesota, Iowa, and central Illinois] and some areas of the region average less than 6 Mg ha^{-1} (90 bu ac^{-1}; counties in southern Missouri, southern Illinois, Kentucky, and eastern Ohio). Normalization was employed to minimize the impact of differing soil properties and farming practices, which vary across the region, upon the statistical prediction of yield. Spatial variation in normalized crop yield is more likely to be dependent on factors that vary widely from year to year, such as rainfall and heat stress, rather than on farming practices and soil characteristics.

d. *Analysis procedures*

For each dataset, county averages were computed for each county with data. For this study, monthly precipitation values were examined because of our primary interest in applications on climate time scales. This has the advantage that issues related to differences in observation times of the cooperative gauges are largely avoided. For all county rainfall estimates, average monthly totals of 0.0 mm were eliminated from the analysis, because a zero value on a monthly scale usually indicates a bad data value. May was selected to represent the springtime planting month, and July was selected to represent the critical pollination period.

All counties with both rainfall data and corn yield data were employed in the analysis. About 750 of the 858 counties in the region were examined each year. The particular counties used in the analysis vary slightly from year to year, depending on whether corn yield or rainfall data were available. The sample sizes are presented in Tables 1 and 2. In 1997, no gridded gauge data were available in Michigan; therefore the gridded MPE for those counties were not included in this study.

In the states west of the study region (Fig. 1), irriga-

TABLE 1. Multiple regression correlation coefficient R, coefficient of determination R^2, number of counties N in sample, and standardized regression coefficients (β, for coefficients significant at the 0.05 level) for normalized corn yield with monthly county rainfall employing multisensor (MPE) and QC_Coop (QC) estimates, and year.

	1997 QC	1998 QC	1999 QC	2001 QC	2002 QC	All QC
R	0.63	0.16	0.43	0.54	0.60	0.47
R^2	0.39	0.02	0.18	0.30	0.36	0.22
N	707	709	695	679	681	3471
Parameters:						
May rain	−0.33				−0.22	−0.20
Jul rain	0.44	0.14	0.43	0.54	0.50	.39
Year	—	—	—	—	—	0.12
	1997 MPE	**1998 MPE**	**1999 MPE**	**2001 MPE**	**2002 MPE**	**All MPE**
R	0.61	0.11	0.43	0.55	0.62	0.49
R^2	0.38	0.01	0.18	0.30	0.38	0.24
N	714	772	750	750	751	3737
Parameters:						
May rain	−0.40	−0.09			−0.24	−0.21
Jul rain	0.33		0.43	0.55	0.52	0.41
Year	—	—	—	—	—	0.12

tion can be an important source of moisture for crops. In the nine-state region considered here, irrigation for the most part is restricted to either seed-corn fields or high-value horticultural crops. Therefore, for this analysis, irrigation is not considered.

3. Results

a. *Yield versus precipitation: Comparison among precipitation estimation methods*

The relationship of normalized corn yield to May and July rainfall for various rainfall estimation methods is presented in Tables 1 and 2. Regression analysis incorporating May and July rainfall resulted in a multiple regression correlation coefficient R of about 0.49 between these factors and normalized corn yield for the MPE precipitation, and 0.47 for the QC_Coop precipitation (Table 1). During individual years, however, R varied from as low as 0.11 in 1998 to 0.62 in 2002, for MPE precipitation.

The correlations between precipitation and normalized corn yield were nearly the same for the MPE and QC_Coop precipitation estimates for all years combined and for individual years. For 2001 and 2002, both the MPE and QC_Coop precipitation estimates were somewhat better related to normalized corn yield than were the RT_Coop estimates (Table 2), presumably because of differences in spatial gauge densities (Fig. 1).

TABLE 2. Same as Table 1, but for relationship between normalized corn yield and monthly county rainfall employing RT_Coop (RT).

	2001 RT	2002 RT
R	0.41	0.55
R^2	0.17	0.30
N	448	446
Parameters:		
May rain	−0.20	−0.27
Jul rain	0.42	0.49

The spatial distribution of rainfall and of the correlation between rainfall and crop yield was examined for the MPE and QC_Coop methods. For each month studied, general agreement was found in the pattern of high and low rainfall amounts from the multisensor-based and quality-controlled cooperative gauge-based data for the Midwest region (not shown). For the five Julys combined (1997–99, 2001–02), a correlation coefficient R of 0.79 was found between the MPE and QC_Coop precipitation fields. Figure 2 presents the spatial distribution of the multiple correlation coefficient R of May and July MPE rainfall with corn yield, for all counties with 5 yr of both crop and rainfall data. Because of the small sample size, none of the correlations are significant. Note, however, that in all areas of the nine-state region, there are contiguous areas where the correlations are 0.5 or more. This same general pattern is found when employing May and July QC_Coop data. The QC_Coop analysis indicates correlation coefficients of 0.5 in Michigan, as well. In addition, the same general pattern over the nine-state region is found when employing normalized corn yield rather than yield. The spatial continuity and the distribution of larger correlations through the study region suggest that even though crop management practices and soil properties vary across the region, corn yield will re-

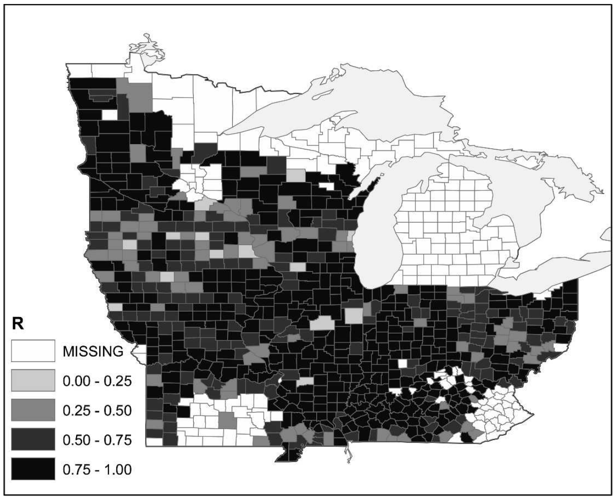

FIG. 2. Shading indicates multiple linear correlation coefficients *R* for May and Jul MPE rainfall with corn yield for counties with 5 yr of data. Missing indicates counties with less than 5 yr of MPE rainfall or crop yield data.

spond to excessive or deficient precipitation in a similar manner.

July precipitation is positively correlated with normalized corn yield, and May precipitation is negatively correlated with normalized corn yield (Table 1). Many studies (e.g., Runge 1968; Thompson 1986) have found that adequate precipitation in July is crucial to good corn yields and that heavy rains during planting season can have a negative impact on corn yield (e.g., Hu and Buyanovsky 2003). Figures 3 and 4 show that moderate to large July precipitation as estimated by MPE or QC_Coop data favors larger yields. Figures 3 and 4 also show that high May rainfall as estimated by both QC_Coop and MPE is detrimental to higher normalized yields.

The similarity in correlation between normalized yield and rainfall as estimated by MPE and QC_Coop for individual years and for all years (Table 1) and the similar response of normalized yield to May and July as estimated by both methods (Figs. 3 and 4) suggest that the MPE and QC_Coop data are of comparable quality for purposes of predicting normalized corn yields. The remaining analysis employs MPE only.

For large normalized corn yields, at least 1.89 Mg ha^{-1} (30 bu ac^{-1}) above the 5-yr mean, May rainfall is generally less than 125 mm and July rain is generally greater than 50 mm (Figs. 3 and 4). For low yields, at least 1.89 Mg ha^{-1} (30 bu ac^{-1}) below the 5-yr mean, July rainfall is generally less than 100 mm. In 1997 and 2002 when the lowest average July rainfall in the nine-state region was observed, the lowest corn yields were observed (Table 3). The normalized yield was particularly low in 2002, when the region experienced a wet spring and a relatively hot and dry July.

Figures 3 and 4 also reveal an area of overlap in the distributions where either very good or very poor yields are found. For example, when May rains are less than 150 mm and corresponding July rains are between 50 and 100 mm, very large and very poor yields can be observed. These results suggest that while precipitation in May and July are important predictors, corn yield predictions may be improved with additional meteorological information.

b. *Heat stress*

Gradients in temperature that are found across the study area also can result in differences in crop growth. To improve the statistical relationship between multisensor-estimated rainfall and yield, an estimate of heat stress has been incorporated into the analysis using stepwise regression. Heat stress days, the average number of days with maximum temperatures ≥32.2°C (90°F) during July, was computed for each county. It was found that when July rainfall was low (e.g., <50–100 mm), high maximum temperatures had a negative impact on normalized corn yield. For lower rainfall totals, the occurrence of more than 10 heat stress days led to low yields (Fig. 5). Inclusion of heat stress improved the relationship between normalized corn yield and rainfall as evidenced by the increase in *R* values (Table 1 and Table 4). The threshold number of heat stress days that affected yields differed from year to year. The *R* values, however, still increased when all years were considered together.

Important to note is that the correlations improved for the two years (1998 and 1999) that had the poorest correlations between rainfall and normalized corn yield. It is interesting that during these two years moderate rain was observed in both May and July—about 100 mm during each month (Table 3). For the five years examined, these two years had the lowest and highest average number of heat stress days. On average, only 5 heat stress days were observed in 1998, and 15 were observed in 1999. With less-stressful conditions in 1998, the normalized yield was the highest of the five years examined. With many days of heat stress but favorable moisture conditions, average crop yields were observed in 1999.

4. Discussion

In the Midwest, high corn yields are associated with low to moderate May rainfall and moderate to high July rainfall (e.g., Thompson 1986; Dharmadhikari et al.

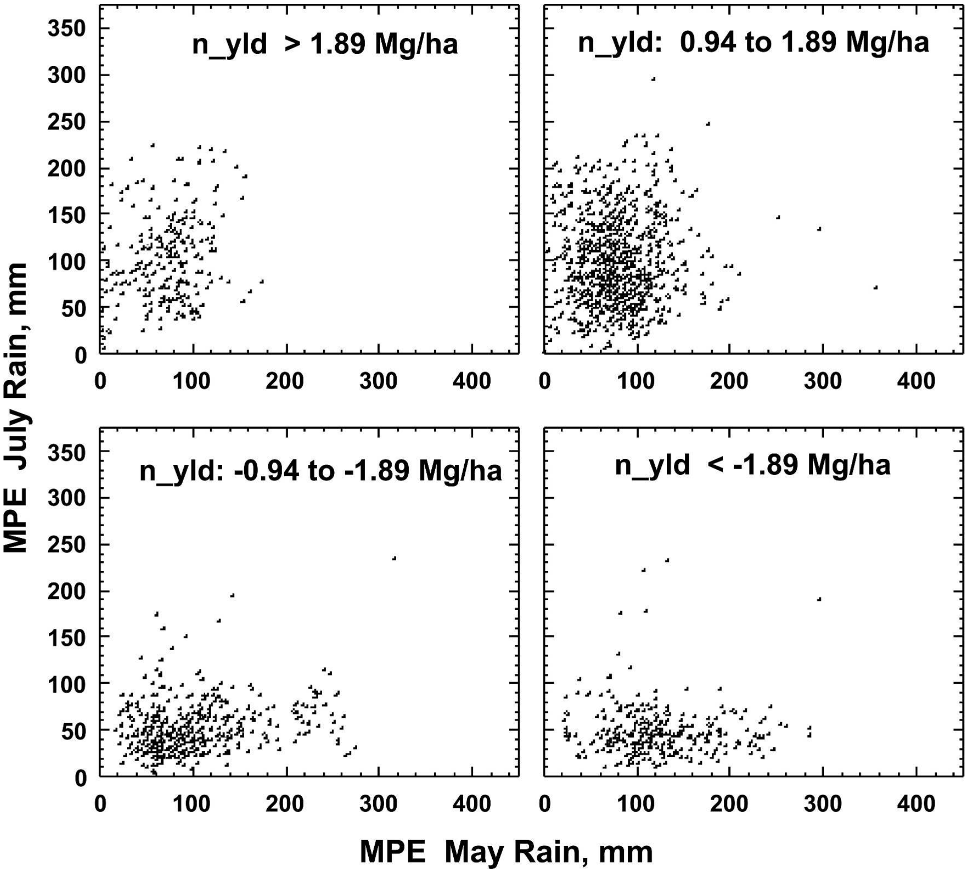

FIG. 3. May and Jul MPE (mm) categorized by normalized corn yield (n_yld; Mg ha^{-1}) by county.

1990). Heavy May rainfall may cause planting delays or necessitate replanting. Later planting dates reduce the length of the growing season and move pollination and grain fill to a period of the season with a higher risk of water and heat stress. These factors contribute to lower yields. Drier soil in May induces deeper root growth because the plants seek adequate water for growth, whereas wet soil encourages the roots to remain in the surface layers of the soil (e.g., Sharp and Davies 1985; Reader et al. 1992). For May county rainfall exceeding 150 mm, about 40% of the counties had normalized corn yields below −0.94 Mg ha^{-1} (−15 bu ac^{-1}), and about 20% of the counties had yields below −1.89 Mg ha^{-1} (−30 bu ac^{-1}).

During July, corn typically will reach the flowering stage when pollen is shed and the silks are fertilized. Ample rainfall in the 2 weeks before and after pollination increases the number of seeds set and increases yield potential. When July rains exceeded 100 mm, normalized corn yields exceeded 0.94 Mg ha^{-1} (15 bu ac^{-1}) in 51% of the counties, and in 12% of the counties yields exceeded 1.89 Mg ha^{-1} (30 bu ac^{-1}). In counties where normalized yields exceeded 1.89 Mg ha^{-1} (30 bu ac^{-1}), July rainfall exceeded 75 mm 72% of the time and exceeded 100 mm 52% of the time.

Temperature also affects crop yield. Heat stress with insufficient rainfall can be detrimental to corn yield (Thompson 1986). In particular, if a wet spring is followed by a dry summer, heat stress can negatively affect plant growth and corn yield. Heat stress affects corn in two ways: 1) high temperatures during pollination reduce the number of seeds set and 2) the evaporative demand of the atmosphere is increased. The results of Herrero and Johnson (1980) suggest that damage done by high temperatures increases as the time interval with high temperatures lengthens. When rainfall during heat stress periods is low, the plant is unable to meet its transpiration demands and photosynthesis is reduced, resulting in decreased yield.

In considering all of the rainfall combinations during the years 1997–99 and 2001–02, the median number of July heat stress days was found to be 9, with about one-quarter of the sample being less than 5 days and about one-quarter of the sample being 15 or more days. Figures 6a and 6b illustrate the impact that heat stress days can have on normalized yields. Muchow et al.

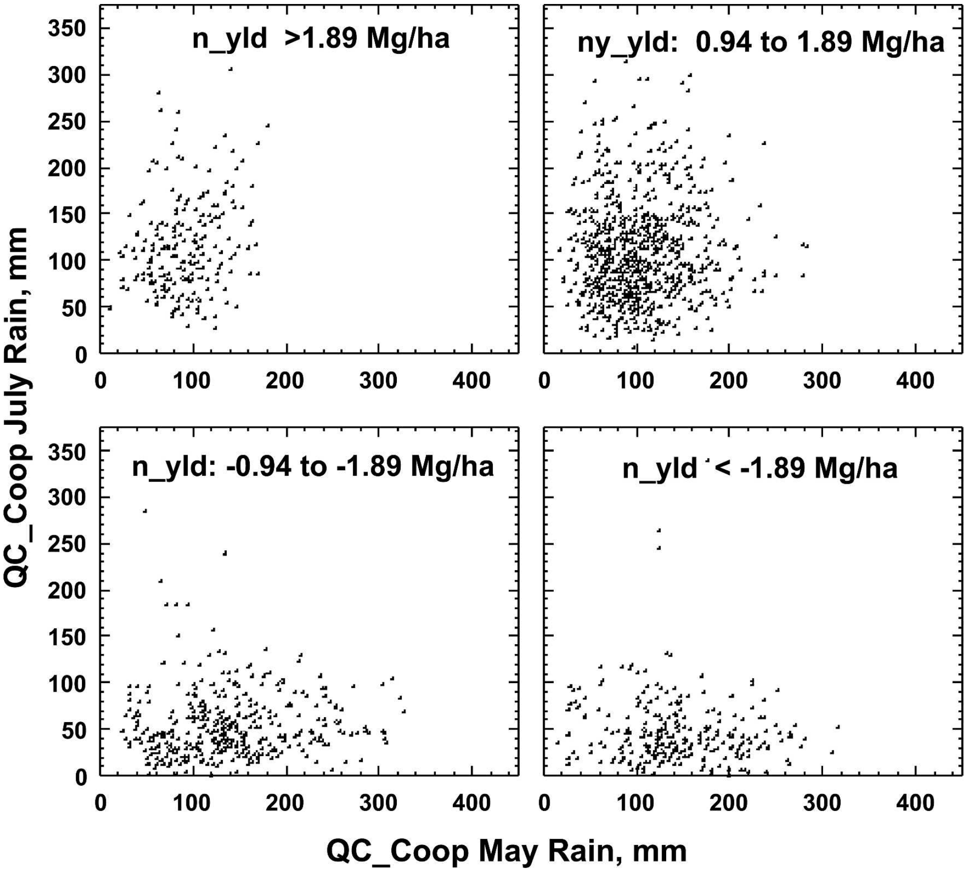

FIG. 4. May and Jul QC_Coop rain estimates (mm) categorized by normalized corn yield (n_yld; Mg ha^{-1}) by county.

(1990) found that lower temperatures in the summer can increase the time a crop intercepts radiation, increasing the duration of crop growth. Hu and Buyanovsky (2003) found for central Missouri that more rainfall and cooler-than-average temperatures in the June–August period were important in high-yield years and that less rainfall and warmer-than-average temperatures during the same months resulted in low yields. Here, when few heat stress days occurred (Fig. 6b), normalized yields were more frequently greater than 0.94 or 1.89 Mg ha^{-1} (15 or 30 bu ac^{-1}). Yields of more than 1.89 Mg ha^{-1} (30 bu ac^{-1}) were found even

TABLE 3. Regional 30-yr (1973–2002) average May and Jul precipitation, Jul mean temperature, and county-averaged values for the study years, based on NWS QC_Coop data. Ranking within 30-yr period is in parentheses. County-averaged number of Jul heat stress days, corn yield, and normalized corn yield (in parentheses) for the study years.

	QC_Coop May rain (mm)	QC_Coop Jul rain (mm)	QC_Coop Jul mean temperature (°C)	No. of heat stress days	Corn yield (Mg ha^{-1}) (normalized; Mg ha^{-1})
Avg	105.4	100.5	22.9		
Std dev	29.2	23.8	1.0		
Max	160.0	168.5	24.6		
Min	46.9	54.6	20.9		
Median	106.6	97.1	22.7		
1997	109.8 (14)	82.9 (26)	22.5 (21)	9	7.37 (0.06)
1998	97.7 (21)	93.6 (17)	22.7 (18)	5	7.88 (0.69)
1999	98.2 (19)	104.3 (12)	24.5 (2)	15	7.62 (0.06)
2001	126.8 (8)	100.2 (14)	23.0 (15)	9	8.25 (0.44)
2002	138.6 (5)	85.8 (21)	24.3 (3)	13	7.43 (−0.57)

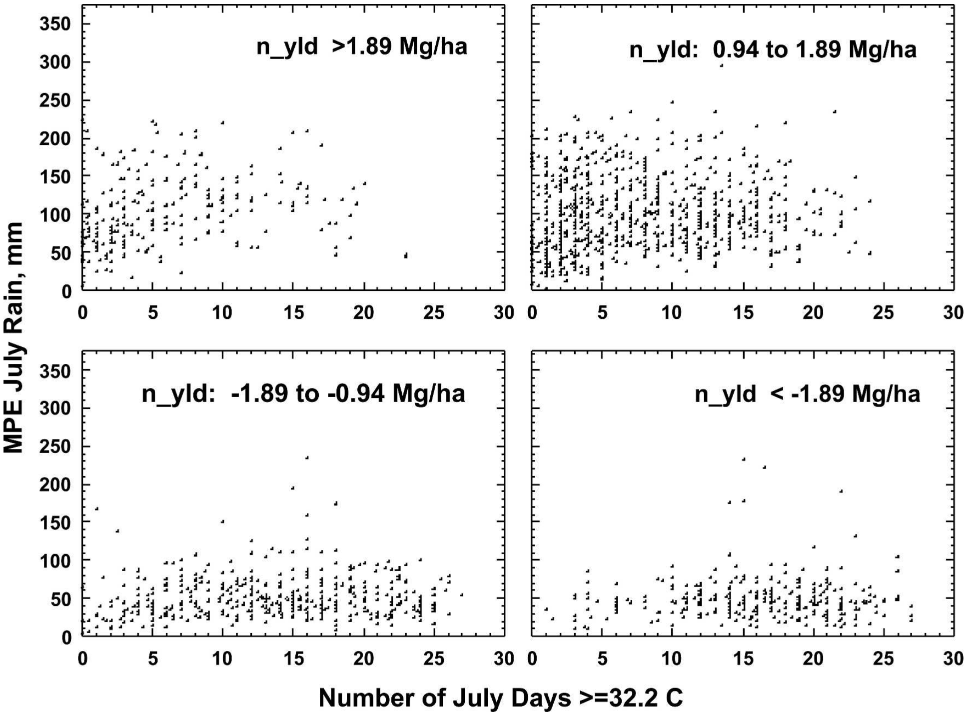

FIG. 5. Number of Jul heat stress days and Jul MPE (mm) categorized by normalized corn yield (n_yld; Mg ha^{-1}) by county.

for July rainfall totals between 25 and 75 mm when few heat stress days were observed. In 1998, when only moderate rainfall was observed on average over the region, the lower temperatures and thus the fewer number of heat stress days likely aided crop yield.

When many heat stress days occurred in July, few counties (Fig. 6a) reported yields exceeding 1.89 Mg ha^{-1} (30 bu ac^{-1}). High temperature with sufficient rainfall was found by Runge (1968) to be beneficial to corn yields. Note that in 2001 the number of heat stress days was positively correlated with normalized corn yield. Although sometimes higher yields were found with more rainfall and many heat stress days (Fig. 6a), higher yields were less frequent under heat stress conditions. Often, more July rainfall was needed to obtain the higher yields when there were many heat stress days.

The response of corn growth to varying rainfall totals differs depending on the location of the rain and heat stress. Because of variability between years in the response of crop yield to rainfall and heat stress, a physically based model, such as the Crop Environment Resource Synthesis (CERES)-Maize model (Jones and Kiniry 1986), may be more appropriate for the prediction of corn yield than a statistically based model. However, the statistical approach used here was appropriate

TABLE 4. Multiple regression correlation (R), coefficient of determination (R^2), number of counties in sample (N), and standardized regression coefficient (ß, 0.05 significance level) for normalized corn yield with number of Jul heat stress days, monthly rain, and year.

	1997 MPE	1998 MPE	1999 MPE	2001 MPE	2002 MPE	All MPE	All QC
R	0.64	0.40	0.62	0.58	0.62	0.56	0.54
R^2	0.41	0.16	0.38	0.34	0.39	0.31	0.29
N	713	765	748	748	749	3723	3462
Parameters:							
May rain	−0.29	−0.09			−0.18	−0.15	−0.16
Jul rain	0.26	0.11	0.14	0.52	0.49	0.35	0.32
Jul 32.2°C days	−0.24	−0.41	−0.53	0.19	−0.11	−0.29	−0.28
Year	—	—	—	—	—	0.06	0.05

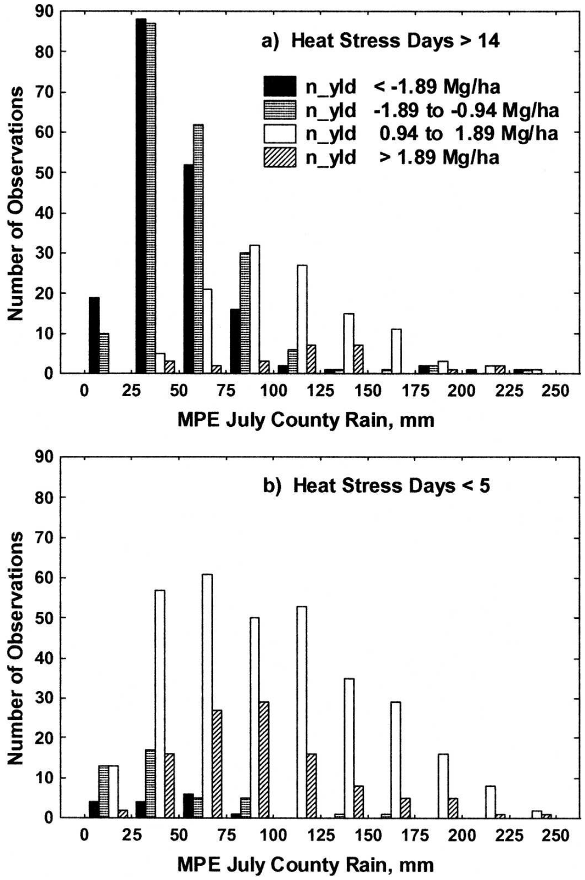

FIG. 6. Frequency of Jul MPE (mm) categorized by normalized corn yield (n_yld; Mg ha^{-1}) (a) when there is an average of more than 14 heat stress days and (b) when there is an average of less than 5 heat stress days per county.

for the purpose of judging the utility of real-time multisensor precipitation estimates for corn yield estimates over hundreds of counties.

5. Summary and conclusions

The relationship between normalized corn yields and monthly rainfall was examined at the county level for a nine-state region of the midwestern United States by employing multisensor and gauge rainfall estimates. For large yields, May rainfall was generally less than 125 mm and July rain was generally greater than 50 mm. For low yields, July rainfall was generally less than 100 mm. However, for moderate July rains of 50–100 mm, both positive and negative normalized yields were common. An estimate of heat stress was incorporated into the analysis. For the two years—1998 and 1999—in which May and July rainfalls were moderate and the correlation between yield and rain was least, the addition of the number of heat stress days greatly improved the results. These results are generally consistent with earlier studies (e.g., Runge 1968; Bauer and Randall 1982; Thompson 1986; Carlson 1990; Hu and Buyanovsky 2003; Chen et al. 2004), but over a larger area and/or over a finer spatial scale.

Multisensor rainfall estimates now are readily available in real time over the United States at a resolution of 4 km. On a monthly basis, they provide an estimate of similar quality to the quality-controlled cooperative network rainfall data that are only available some months after the growing season is over. Further, the multisensor data are available at a finer spatial resolution than the real-time cooperative network data. Applying these high-resolution MPE rain values to physiologically based models in near–real time should improve in-season estimates of the final corn yields and provide valuable information about where the greatest production may be located. Knowing where the greatest production may occur will allow the distribution system to prepare for timely movement of the crop to production and export facilities.

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