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Creating long-term weather data from thin air for crop simulation modeling

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ABSTRACT

Simulating crop yield and yield variability requires long-term, high-quality daily weather data, including solar radiation, maximum (T_{max}) and minimum temperature (T_{min}), and precipitation. In many regions, however, daily weather data of sufficient quality and duration are not available. To overcome this limitation, we evaluated a new method to create long-term weather series based on a few years of observed daily temperature data (hereafter called propagated data). The propagated data are comprised of uncorrected gridded solar radiation from the Prediction of Worldwide Energy Resource dataset from the National Aeronautics and Space Administration (NASA–POWER), rainfall from the Tropical Rainfall Measuring Mission (TRMM) dataset, and location-specific calibration of NASA–POWER T_{max} and T_{min} using a limited amount of observed daily temperature data. The distributions of simulated yields of maize, rice, or wheat with propagated data were compared with simulated yields using observed weather data at 18 sites in North and South America, Europe, Africa, and Asia. Other sources of weather data typically used in crop modeling for locations without long-term observed weather data were also included in the comparison: (i) uncorrected NASA–POWER weather data and (ii) generated weather data using the MarkSim weather generator. Results indicated good agreement between yields simulated with propagated weather data and yields simulated using observed weather data. For example, the distribution of simulated yields using propagated data was within 10% of the simulated yields using observed data at 78% of locations and degree of yield stability (quantified by coefficient of variation) was very similar at 89% of locations. In contrast, simulated yields based entirely on uncorrected NASA–POWER data or generated weather data using MarkSim were within 10% of yields simulated using observed data in only 44 and 33% of cases, respectively, and the bias was not consistent across locations and crops. We conclude that, for most locations, 3 years of observed daily T_{max} and T_{min} data would allow creation of a robust weather data set for simulation of long-term mean yield and yield stability of major cereal crops.

1. Introduction

Due to year-to-year fluctuation in weather patterns, long-term daily weather data, including solar radiation, temperature (maximum [T_{max}] and minimum [T_{min}]), and precipitation, are required to estimate crop yield potential and its variability using crop simulation models (Whisler et al., 1986; Boote et al., 1996; van Bussel et al., 2011 Van Wart et al., 2013a). Such estimates of yield potential and its variability are essential for analysis of food security, assessing impact of climate change on crop production, development and use of crop management decision-support tools, and to support and target agronomic research and policy. Depending on the degree of weather variability among years, at least 10–20 years of daily weather data are necessary for reliable estimates of mean yield potential and its inter-annual variability (van Ittersum et al., 2013 ; Van Wart et al. 2013a; Grassini et al., 2015). In many parts of the world, however, most weather stations only have a few years of daily weather records available and often not all of

Abbreviations: GridWD, gridded weather data; GenWD, generated weather data; RH, relative humidity; T_{min}, minimum temperature; T_{max}, maximum temperature; T_{dew}, dew point temperature; ETo, grass-based reference evapotranspiration; OWD, observed weather data; PWD, propagated weather data.

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the variables necessary for crop model simulations are measured (*e.g.*, incident solar radiation). Unfortunately, many regions with limited availability of weather data (*e.g.*, Sub-Saharan Africa) are of greatest concern with regard to food security and vulnerability to climate change (Lobell et al., 2008). Hence, it is important to develop methods for generating reliable, long-term weather data for these regions where availability of weather data severely limits ability to perform robust assessments of yield gaps, and food security scenarios.

Gridded weather data (GridWD) or generated weather data (GenWD) have been used as alternatives in regions where observed weather data (OWD) are not available (Table 1). Crop simulation studies relying on GridWD and GenWD, however, have rarely compared simulated yields against simulations using OWD from weather stations located within the area of study. However, this is crucial because, in generating long-term weather data with global spatial coverage, sources of error can be incorporated into both GridWD and GenWD that can result in biased estimates of crop yield and its variability over time.

GridWD are typically derived by interpolation of observed weather data over space, or may also be derived from global climate models, to estimate daily or monthly weather data for each individual grid cell of land area (Kanamitsu et al., 2002; New et al., 2002). The quality of the estimation for a given grid cell depends on the density and distribution of the weather stations used in its derivation. Because both density and distribution are far from satisfactory in many regions of the world, derived GridWd in these regions are subject to a large degree of uncertainty. In fact, even in regions with an adequate density of weather stations, poor agreement has been found between simulated crop yields using GridWD *versus* simulations using OWD from a location within the same grid cell (Mearns et al., 2001; Baron et al., 2005). Regardless of whether the GridWD are derived through interpolation or from climate models, the bias in simulated yields using GridWD, relative to yields simulated using OWD, has been found to be unpredictable and inconsistent, having different sign and magnitude across locations for temperature and rainfall (Van Wart et al., 2013b).

A stochastic weather generator produces synthetic time series of daily weather data (GenWD) for as many years as specified for a location based on the statistical characteristics of historical daily or monthly OWD at that location (Hutchinson, 1987; Jones and Thornton, 2000; Hansen and Mavromatis, 2001; Mavromatis and Hansen, 2001). Models for generating stochastic weather data are typically developed in two steps: the first step is to model daily precipitation and the second step is to model or estimate the remaining variables of interest, such as daily T_{max} and T_{min}, solar radiation, humidity and wind speed. Even when decades of daily OWD are used to calibrate weather generators, they may perform poorly when compared to simulated crop yields based on OWD and typically underestimate inter-annual variation in crop model simulations (Semenov and Porter, 1995; Hammer et al., 2002). Likewise, though monthly means and variances of GenWD and OWD may be similar, short periods of extreme events, which are of particular importance for crop growth, yield and even crop failure, are typically not well represented in generated data (Kyselý and Dubrovsky, 2005; Semenov, 2008). While there are continuing efforts to improve weather generators, such efforts are constrained by the number of years and sites required for their parameterization (Baigorria and Jones, 2010; Rosenzweig et al., 2013).

Daily OWD with sufficient number of years to simulate long-term average crop yield and its variability (>10 years) are not available for many regions of the world. In contrast, short-term OWD of several years duration (typically <5 years) with daily maximum and minimum temperature (T_{max} and T_{min}, respectively) is often available for most regions. For example, in Africa there are a total of 1048 meteorological stations reporting at least 3 years of publically available weather data, but less than 12% of these stations have at least 15 years of OWD of adequate quality (missing <10% of total data and with no more than 30 data days missing consecutively) for crop simulation (National Climate Data Center, 2014). As an alternative to the use of GridWD or GenWD, here we present a protocol that utilizes 3 years of observed T_{max} and T_{min} data, combined with long-term GridWD of solar radiation and precipitation, to generate a long-term daily weather data set suitable for simulation of crop yields (hereafter called 'propagated' weather data [PWD]). The purpose of this paper is to evaluate how simulated yields compare when using PWD *versus* (i) OWD, (ii) GridWD and (iii) GenWD. In the present paper, the comparison was made across 18 sites, located in four continents (Europe, Asia, America, and Africa), for which long-term, high-quality daily OWD were available. Simulated crops include three major cereals (maize, rice and wheat), each simulated with well-validated crop models and based on site-specific soil properties and crop management to ensure agronomic relevance.

Table 1
Studies that used gridded or generated weather data for agricultural research in Sub-Saharan Africa.

Database	References
Gridded weather data	
CRU[a]	(Fischer et al., 2002; Foley et al., 2005; Bondeau et al., 2007; Lobell, 2007; Lobell et al., 2008; Battisti and Naylor 2009; Licker et al., 2010; Folberth et al., 2012; Folberth et al., 2013)
NASA[b]	(Folberth et al., 2012; Arndt et al., 2012)
NCEP[c]	(Lobell and Asner 2003; Nemani et al., 2003; Bagley et al., 2012)
WorldClim[d]	(Thornton et al., 2009; Nelson et al., 2010; Claessens et al., 2012)
Other[e]	(Jones and Thornton, 2003; Stéphenne and Lambin, 2001; Lobell et al., 2008; Rowhani et al., 2011)
Weather generators	
MarkSim	(Mavromatis and Hansen, 2001; Jones and Thornton, 2003; Thornton et al., 2009; Claessens et al., 2012)
WGEN (WeatherMan)	(Mavromatis and Hansen, 2001; Li et al., 2005; Schoul et al., 2008)
ClimGen	(Abraha and Savage, 2006; Laux et al., 2010)

[a] Climate Research Unit (CRU) http://badc.nerc.ac.uk/data/cru/.
[b] National Aeronautics and Space Administration (NASA) http://power.larc.nasa.gov/.
[c] National Center for Environmental Prediction/Department of Energy (NCEP) http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.html.
[d] WorldClim http://www.worldclim.org/.
[e] All future climate data as modeled by global climate models, distributed by the International Panel on Climate Change (IPCC) http://www.ipcc-data.org/.

2. Materials and methods

2.1. Evaluation of NASA gridded data

The Prediction of Worldwide Energy Resource (POWER) dataset from the National Aeronautics and Space Administration (NASA, 2012), hereafter called NASA, was selected as the GridWD source for use in this study because it is publically accessible, shows general acceptable agreement with ground data for incident solar radiation, and has been used in previous studies that have simulated crop yields (Bai et al., 2010 Van Wart et al., 2013a,b). The NASA dataset contains daily incident solar radiation, T_{max}, T_{min}, dew point temperature (T_{dew}), precipitation, wind speed, and relative

Table 2
Meteorological station name, latitude and longitude (in decimal degrees), years of available weather data, and measured weather variables.

Site & country	Latitude	Longitude	Years	Measured weather variables
Eastern Asia				
Gushi (China)	32.1	115.4	1990–2010	T_{min}, T_{max}, radiation, precipitation
Chongqing (China)	29.35	106.28	1990–2010	T_{min}, T_{max}, radiation, precipitation
Nanning (China)	22.38	108.13	1990–2010	T_{min}, T_{max}, radiation, precipitation
Sub-Saharan Africa				
Dedougou (Burkina Faso)	12.47	−3.48	1998–2007	T_{min}, T_{max}, radiation, precipitation
Gaoua (Burkina Faso)	10.33	−3.18	1998–2007	T_{min}, T_{max}, radiation, precipitation
Chapata (Zambia)	−13.56	32.59	1998–2011	T_{min}, T_{max}, precipitation
Choma (Zambia)	−16.81	26.97	1998–2011	T_{min}, T_{max}, precipitation
Katumani (Kenya)	−1.55	37.32	1998–2005	T_{min}, T_{max}, precipitation
Embu (Kenya)	−0.54	37.45	1998–2007	T_{min}, T_{max}, precipitation
Melkassa (Ethiopia)	8.4	39.33	1998–2005	T_{min}, T_{max}, radiation, precipitation
North America				
North Platte (USA)	41.08	−100.77	1998–2011	T_{min}, T_{max}, radiation, precipitation, relative humidity
Mead (USA)	41.25	−96.58	1998–2011	T_{min}, T_{max}, radiation, precipitation
Dekalb (USA)	41.84	−88.85	1998–2011	T_{min}, T_{max}, radiation, precipitation, relative humidity
Bondville (USA)	40.05	−88.37	1998–2011	T_{min}, T_{max}, radiation, precipitation
Europe				
Leipzig (Germany)	51.48	12.28	1998–2007	T_{min}, T_{max}, radiation, precipitation
Dusseldorf (Germany)	51.43	6.77	1998–2007	T_{min}, T_{max}, radiation, precipitation
South America				
Oliveros (Argentina)	−32.33	−60.51	1998–2009	T_{min}, T_{max}, radiation, precipitation
Balcarce (Argentina)	−37.8	−58.3	1998–2010	T_{min}, T_{max}, radiation, precipitation

humidity (RH) data for each $1^\circ \times 1^\circ$ grid (approximately 111 km^2 at the equator) of the entire globe starting in 1983, though precipitation data are not reported until 1997 (Chandler et al., 2004). These data are derived from satellite observations coupled with the Goddard Earth Observing System climate model to obtain complete terrestrial coverage.

We evaluated NASA weather data against OWD from 18 meteorological stations (Table 2). Selection of sites was based on (i) location in a region with large production area of maize, rice, or wheat, (ii) availability of complete daily records for all meteorological variables required for crop yield simulation, including T_{min}, T_{max} and precipitation, with few erroneous or missing days, and (iii) availability of data on crop management and soil properties surrounding each weather station. Required inputs to run crop simulation models, including crop sowing dates, cultivar maturity and phenology, plant population, and soil properties governing rooting depth and water holding capacity, were obtained from the Global Yield Gap Atlas (www.yieldgap.org). For each weather variable (solar radiation, T_{max}, T_{min}, T_{dew}, RH, and precipitation), we evaluated the degree of correlation and agreement between OWD and NASA data for the grid cell in which weather stations were located. The intercept (b), slope (m), and coefficient of determination (r^2) of the linear regression were calculated to determine the strength and bias of the relationship, while the root mean square error (RMSE) was computed to measure the degree of agreement between data sources:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \tag{1}$$

where x_i and y_i are NASA and OWD for a given variable, respectively, for day i and n is the total number of days included.

In addition to the NASA data, we also analyzed precipitation as recorded by the Tropical Rainfall Measuring Mission (TRMM), which uses satellite data to derive historical rainfall events over a finer spatial grid ($\sim$5 km^2) (Kummerow et al., 2000). Because simulated non-irrigated yields are more sensitive to differences in total precipitation and its distribution during a period of several weeks than to differences in daily rainfall amounts, the comparison of precipitation in NASA or TRMM and precipitation in OWD was performed separately for daily values and 2-week totals. We also evaluated the prevalence of false wet days in NASA and TRMM (a precipitation event reported by the GridWD but not recorded in the OWD) and false dry days (a precipitation event not reported by GridWD but recorded in the OWD). Due to uncertainties in the precipitation measurements and the relatively minor impact of very small precipitation events on simulated yields, only precipitation events >6 mm were considered for the analysis of dry and wet days (Sadras, 2003 and references cited therein). Moreover, because weather stations may record 24-h total precipitation for different times (midnight-to-midnight *versus* noon-to-noon), the previous analysis was also performed considering a 3-day interval centered on the wet day reported by OWD. Using log-transformed values of rainfall in the above linear regression analysis changed little the estimates of b, m and r^2 values, hence, we only show the analysis based on the untransformed data.

2.2. Creation and evaluation of propagated and generated long-term weather records

For each selected weather station, the OWD were compared with NASA data for the grid in which the weather station was located using linear regression and calculating RMSE. When there was strong correlation ($r^2 > 0.7$) and good agreement with OWD (RMSE <30% of OWD mean), with little bias (m from 0.8 to 1.2, $b < 2\%$ of OWD mean), NASA data for that variable were used directly for creating long-term weather records for crop simulation. Similar cutoffs have been used in previous studies to assess associations between weather variables (*e.g.*, Mahmood and Hubbard, 2002; Hubbard and You, 2005). For those meteorological variables from NASA that exhibited strong correlation ($r^2 > 0.7$) but poor agreement (RMSE >30% of the OWD mean) or consistent bias ($m < 0.8$ or >1.2 and $b > 2\%$ of OWD mean), correction was made using OWD. The previous correction is needed to bring NASA values in closer agreement to observed values, and thus, be more useful for crop modelling. For correction of each variable, a linear regression equation was generated with OWD taken as the dependent variable (y) and NASA data as the independent variable (x). The slope and intercept from the regression equation $y = mx + b$ were used to produce a corrected estimate of these data ($\hat{y}$). The NASA variables that did not require correction were then combined with the corrected variables to create a complete weather dataset for each weather station that included all variables required for crop modeling (solar radiation, T_{max}, T_{min}, precipitation, and RH) and for the same time interval as the OWD as given in Table 2. These databases comprise the PWD.

For situations in which weather data are scarce, it is not known a priori how many years or the specific time period for which OWD are available to serve as basis for calibration of NASA data to generate the long-term PWD. At issue, therefore, is how sensitive PWD are to the number of years (*e.g.*, 3, 5, or 10 years) or time period (*e.g.*, 1990–1992 *versus* 1993–1995 or any other 3-year interval within the time series) of OWD used to calibrate NASA data. To evaluate this sensitivity, we calibrated NASA data based on all possible subsets of 3, 4, 5, and 10 consecutive years of OWD at each location, which resulted in multiple PWD files for use in crop simulation for that site. On average, across crop-country cases, there were 11, 10, 9 and 5 PWD files created based on 3, 4, 5, and 10 years of consecutive OWD, respectively. The resulting PWD files were then used to simulate crop yield potential at each location, resulting in a distribution of possible simulated yields depending on the specific years selected for correction of NASA data.

MarkSim is the most widely used weather generator to create long-term weather data for crop yield simulations (*e.g.*, Mavromatis and Hansen, 2001; Jones and Thornton, 2003; Thornton et al., 2009; Claessens et al., 2012 ; Jones and Thornton, 2013). To generate a long-term weather database for a given location using the MarkSim weather generator requires geographic coordinates of the site, monthly mean T_{max}, T_{min}, and precipitation, as well as the average number of precipitation events in each month (Jones and Thornton, 2000). In the present paper, these monthly means were calculated for each of the 18 locations over the entire time-span of available OWD (Table 2). These monthly means were then used in the MarkSim model to generate the recommended 50 years of synthetic data, which were then used as input to the crop simulation models for simulation of long-term average yield potential and its variability over time for the same time interval as the available OWD.

For each weather station site, we compared long-term mean simulated yields using PWD, NASA or MarkSim weather data against yields simulated using OWD. We also evaluated the coefficient of variation (CV) of simulated yields estimated using the different weather databases. Comparisons in terms of simulated crop yield potential, and its variability, provide a robust evaluation of the weather datasets in terms of usefulness for crop modelling (White et al., 2008a; Bai et al., 2010; Van Wart et al., 2013b). The simulated yields with OWD are presented in horizontal box plots for each of the 18 crop-country cases whereby the boxplots plus associated whiskers show the distribution of possible PWD yields based on different subsets of years of OWD used to calibrate NASA data as described in. Uncorrected NASA data coupled with TRMM precipitation were also used in simulations and compared with simulations using PWD to assess the impact of source of precipitation data on simulations compared with OWD.

2.3. Crop simulation modeling

Crop yields were simulated using ORYZA2000, Hybrid-Maize, or CERES-Wheat simulation models for rice, maize and wheat, respectively (Bouman et al., 2001; Yang et al., 2004; Ritchie et al., 1988). These models have been widely used, calibrated and evaluated in a wide range of environments against yields from field experiments in which crops received optimal management (Ghaffari et al., 2001; Bouman and van Laar 2006; Grassini et al., 2009). Each of these mechanistic models operates on a daily-time step and requires daily T_{max}, T_{min}, and solar radiation to simulate irrigated yield potential (*i.e.*, without water stress) and also precipitation to simulate rainfed yield potential. Reference grass-based evapotranspiration (ETo) was calculated using the Penman–Monteith–FAO method, assuming wind speed equal to 2 m s^{-1} (Allen et al., 1998). In this study, simulated grain yields are reported at standard moisture contents of 0.140, 0.155, and 0.135 kg H_2O kg^{-1} grain for rice, maize and wheat, respectively.

Model inputs necessary for simulating crop yields include soil properties (soil texture, soil rooting depth, and bulk density), management practices (cultivar maturity, sowing date, and plant population), and genotype-specific coefficients for adapted crop cultivars or hybrids at each location. These parameters were taken from Van Wart et al. (2013a) for sites in USA, Germany and China. Required model inputs for locations in other countries were provided by agronomic experts who collaborated on the Global Yield Gap Atlas (www.yieldgap.org). Maturity and phenological coefficients were estimated for all models based on OWD, separately for each site, and then these coefficients were used for all other simulations for that site with other weather data sources (PWD or GridWD). All model input data (management, soils and

Table 3
Slope (m), intercept (b), and coefficient of determination (r^2) for the linear regression between gridded NASA (independent variable) *versus* weather-station observed data (dependent variable) for solar radiation (SR) and minimum and maximum temperature (T_{max} and T_{min}, respectively) for each of the 18 sites examined in the present study. The root mean square error (RMSE) is also shown. At some locations the solar radiation was not recorded (n.a.).

	SR (MJ m^{-2} d^{-1})				T_{max} (°C)				T_{min} (°C)			
Site	b	m	r^2	RMSE	b	m	r^2	RMSE	b	m	r^2	RMSE
Gushi	0.0	0.9	0.7	5.0	−1.6	1.0	0.9	2.7	0.1	1.0	1.0	2.2
Chongqing	−1.6	0.9	0.9	4.3	4.8	0.9	0.9	4.3	5.5	0.8	0.9	4.1
Nanning	−0.8	1.0	0.7	3.7	2.4	1.0	0.8	3.6	2.0	0.9	0.9	2.4
Dedougou	n.a.	n.a.	n.a.	n.a.	9.1	0.8	0.7	2.7	2.1	0.9	0.6	2.1
Gaoua	n.a.	n.a.	n.a.	n.a.	10.9	0.7	0.6	3.3	−6.0	1.3	0.5	2.6
Chapata	n.a.	n.a.	n.a.	n.a.	14.9	0.5	0.5	3.4	3.8	0.7	0.6	2.4
Choma	n.a.	n.a.	n.a.	n.a.	11.6	0.5	0.4	4.1	−4.3	1.0	0.6	4.9
Katumani	n.a.	n.a.	n.a.	n.a.	6.5	0.7	0.3	2.5	8.0	0.3	0.1	4.2
Embu	n.a.	n.a.	n.a.	n.a.	9.6	0.6	0.2	2.7	6.2	0.5	0.2	2.4
Melkassa	10.4	0.5	0.2	4.3	10.8	0.7	0.4	5.0	0.0	0.9	0.3	3.6
NorthPlatte	0.3	0.9	0.9	2.4	2.8	1.0	0.9	3.9	−1.7	1.0	0.9	3.4
Mead	0.2	0.9	0.9	2.8	2.2	1.0	0.9	3.3	−1.4	1.0	0.9	3.2
Dekalb	0.3	1.0	0.9	2.3	−0.1	1.0	1.0	2.7	−1.9	0.9	1.0	3.4
Bondville	0.7	1.0	0.9	2.9	1.1	0.9	1.0	2.5	−1.3	0.9	0.9	3.2
Leipzig	−0.3	1.1	1.0	2.0	1.9	0.9	1.0	2.1	0.8	0.9	0.9	2.0
Dusseldorf	0.0	1.0	1.0	1.6	1.9	0.9	1.0	1.9	1.0	1.0	0.9	2.1
Oliveros	3.2	0.8	0.8	4.6	3.8	0.8	0.8	3.3	−0.3	1.0	0.8	3.0
Balcarce	2.3	0.7	0.7	5.2	1.8	0.9	0.9	2.6	−0.2	0.9	0.9	2.0

crop cultivar coefficients) used in the simulations are provided in Tables S1–S3. The range of long-term average simulated yields across site-crop cases in the present study (from 4.8 to 16.5 t ha^{-1}) is representative of variation in potential yield across cropping systems and environments with varying climate and soil conditions. For example, the lower limit of the simulate yield potential range in this study coincides with the yield potential expected for rainfed cropping systems in harsh rainfed environments, such as wheat in Australia, whereas the upper limit is typical of potential yields for non-water limited cropping systems as found in favorable rainfed or irrigated maize production areas in the U.S. Corn Belt and Great Plains (van Ittersum et al., 2013)

3. Results

3.1. Comparison of uncorrected NASA and observed weather data

NASA solar radiation exhibited a good agreement with OWD solar radiation at all locations (r^2 = 0.85, m = 0.90 and b = 0.38, averaged across all other sites), except for Melkassa, Ethiopia, which is a site with mountainous topography (Table 3). This finding is consistent with previous results reported by White et al. (2008b), Bai et al. (2010), and Van Wart et al. (2013b), who found very good agreement between NASA solar radiation and ground observations for regions with relatively uniform flat topography, while the agreement was poorer in regions with heterogeneous topography. In contrast, NASA T_{max} and T_{min} exhibited a strong bias in 78% of the cases as indicated by either slopes or intercepts largely different from one and zero, respectively (Table 3). The type of bias for NASA T_{max} and T_{min} was inconsistent, with different signs and magnitudes across locations. At nine sites, the direction of bias differed for T_{min} *versus* T_{max}. For example, at North Platte, NASA T_{min} was lower than OWD by about 1.7 °C while NASA T_{max} was higher than OWD by 2.8 °C. In contrast, at Embu both NASA T_{min} and T_{max} were substantially higher than OWD T_{min} and T_{max} (6.2 and 9.6 °C, respectively). White et al. (2008a) also found biases between OWD and NASA temperature and speculated that these can be attributed to variation in elevation, landscape position, presence of large bodies of water, or problems with the assimilation model used to derive the NASA temperature data. Hence, it seems that variation in the sign and magnitude of the bias in NASA temperature data is highly unpredictable across locations. Despite this inconsistent bias, there was a strong correlation between NASA and OWD T_{max} and T_{min} (r^2 from 0.78 to 0.96 for T_{max} and 0.79 to 0.95 for T_{min}), except for the locations in Sub-Saharan Africa where consistently weaker relationships were found (r^2 from 0.21 to 0.67 for T_{max} and 0.05 to 0.64 for T_{min}). The weakest temperature correlations occurred at sites with complex topography in Kenya and Ethiopia (total of 3 sites, with average r^2 of 0.29 and 0.19 for T_{max} and T_{min}, respectively).

Estimation of ETo using the Penman–Monteith–FAO method requires some measure of humidity, such as RH or T_{dew}. However, many meteorological stations do not measure these variables; only 7 of the OWD stations used in our study recorded T_{dew} and only 13 recorded RH (Table 4). Across all sites where data were available, agreement between uncorrected NASA- and OWD-T_{dew} was much stronger (mean r^2 = 0.80 across the seven locations with T_{dew} values) than between uncorrected NASA- and OWD-RH (mean r^2 = 0.40 across the 13 locations with RH values) (Table 4). Likewise, regression slopes of NASA- *versus* OWD-T_{dew} were consistently

Table 4
Slope (m), intercept (b), and coefficient of determination (r^2) for the linear regression between gridded NASA (independent variables) *versus* observed data from a meteorological station (dependent variable) for relative humidity and dew point temperature (T_{dew}) for sites examined in the present study. Data were not recorded at some locations (n.a.). The root mean square error (RMSE) is also shown.

Sites	RH (%)				T_{dew} (°C)			
	b	m	r^2	RMSE	b	m	r^2	RMSE
Gushi	4	0	0.6	59	2.1	0.9	1.0	2.6
Chongqing	5	0	0.3	68	3.7	0.9	1.0	3.2
Nanning	4	0	0.4	71	n.a.	n.a.	n.a.	n.a.
Dedougou	n.a.	n.a.	n.a.	n.a.	3.4	0.9	0.9	4.1
Gaoua	n.a.	n.a.	n.a.	n.a.	4.2	0.8	0.8	4.5
Chapata	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Choma	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Katumani	36	0	0.2	44	n.a.	n.a.	n.a.	n.a.
Embu	49	0	0.1	41	7.1	0.5	0.4	2.1
Melkassa	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
North Platte	24	1	0.5	13	0.9	1.0	0.9	2.6
Mead	47	0	0.1	17	n.a.	n.a.	n.a.	n.a.
Dekalb	58	0	0.2	20	2.6	0.8	0.7	6.6
Bondville	43	1	0.5	16	n.a.	n.a.	n.a.	n.a.
Leipzig	31	1	0.6	41	n.a.	n.a.	n.a.	n.a.
Dusseldorf	26	1	0.6	41	n.a.	n.a.	n.a.	n.a.
Oliveros	52	0	0.4	25	n.a.	n.a.	n.a.	n.a.
Balcarce	42	1	0.5	24	n.a.	n.a.	n.a.	n.a.

Table 5
Slope (m), intercept (b), and coefficient of determination (r^2) for the linear regression between gridded NASA and TRMM (independent variables) *versus* observed data from a meteorological station (dependent variable) for daily (NASA-1, TRMM-1) and 14-day (NASA-14, TRMM-14) total precipitation (mm) for each of the18 sites examined in the present study. TRMM data were not available (n.a.) for some sites. The root mean square error (RMSE) is also shown.

Site	NASA-1				NASA-14				TRMM-1				TRMM-14			
	B	m	r^2	RMSE	b	m	r^2	RMSE	b	m	r^2	RMSE	b	m	r^2	RMSE
Gushi	2	0	0.1	11	7	1	0.5	39	2	0	0.2	11	7	1	0.7	32
Chongqing	2	0	0.1	11	11	1	0.5	38	2	0	0.1	12	12	1	0.6	35
Nanning	2	0	0.2	12	7	1	0.6	48	2	0	0.3	12	6	1	0.8	39
Dedougou	1	1	0.2	7	2	1	0.8	22	1	0	0.2	8	5	1	0.7	25
Gaoua	1	1	0.2	9	4	1	0.7	26	2	0	0.2	10	6	1	0.7	25
Chapata	4	0	0.0	11	0	1	0.6	53	1	1	0.2	12	1	1	0.6	55
Choma	2	0	0.0	7	1	1	0.8	23	1	1	0.2	7	2	1	0.8	23
Katumani	1	1	0.2	7	9	1	0.6	27	1	0	0.2	8	8	1	0.7	32
Embu	2	1	0.1	10	17	1	0.5	55	2	0	0.2	10	11	1	0.7	40
Melkassa	1	0	0.1	7	11	1	0.4	33	1	0	0.1	7	8	1	0.4	30
North Platte	1	0	0.1	5	6	1	0.3	24	1	0	0.1	6	1	1	0.6	18
Mead	1	0	0.2	7	7	1	0.3	29	1	0	0.2	8	2	1	0.6	23
Dekalb	1	0	0.1	8	2	1	0.4	30	1	0	0.2	9	8	1	0.5	29
Bondville	1	0	0.2	8	19	0	0.2	37	1	0	0.2	9	8	1	0.5	29
Leipzig	1	0	0.0	9	19	0	0.1	50	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Dusseldorf	2	0	0.1	9	27	0	0.1	52	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Oliveros	3	0	0.1	20	5	1	0.6	29	1	0	0.3	11	10	1	0.6	34
Balcarce	2	0	0.1	10	10	1	0.4	33	2	0	0.1	10	7	1	0.6	25

Table 6
Prevalence of false wet (precipitation >6 mm) and false dry days in NASA and TRMM gridded weather data for each of the 18 sites examined in the present study. TRMM data were not available (n.a.) for high-latitudes sites.

	NASA			TRMM		
Site	% False wet days	% False dry days	% False dry (3-day interval)[a]	% False wet days	% False dry days	% False dry (3-day interval)[a]
Gushi	5	9	7	4	9	7
Chongqing	6	10	8	5	10	7
Nanning	7	8	6	5	8	7
Dedougou	7	5	2	5	5	3
Gaoua	10	6	2	7	6	3
Chapata	8	5	3	8	5	2
Choma	6	5	3	5	5	2
Katumani	4	5	3	5	4	2
Embu	4	10	7	6	8	4
Melkassa	10	6	4	9	6	4
North Platte	6	4	3	5	4	2
Mead	8	4	3	6	4	2
Dekalb	11	5	4	7	5	2
Bondville	10	6	4	7	5	2
Leipzig	11	4	2	n.a.	n.a.	n.a.
Dusseldorf	11	6	3	n.a.	n.a.	n.a.
Oliveros	5	5	3	4	5	2
Balcarce	7	7	4	6	6	3

[a] Based on 3-day intervals centered on the observed wet day.

closer to unity (mean of $b = 0.83$ across the seven locations) compared with NASA- *versus* OWD-RH (mean b of 0.39 across the 13 locations). Therefore, to estimate the measure of humidity required by each crop simulation model, we used the uncorrected NASA T_{dew} given the high r^2 and slope near unity between NASA- and OWD-T_{dew} values.

Calibration of daily rainfall from NASA or TRMM was not feasible due to the low correlation, poor agreement, and strong bias in the relationship between daily precipitation in these GridWD sources and daily precipitation values in the comparable OWD (Table 5). Compared to OWD, TRMM data had much stronger agreement with 14-day total rainfall *versus* NASA precipitation (mean r^2 of 0.62 *versus* 0.45 with mean RMSE = 36 mm *versus* 31 mm). TRMM also performed better than NASA data with regard to timing of precipitation events: TRMM has a frequency of false wet days, on average, 2–3% lower than for NASA, while there was no difference between the two data sources in the frequency of false dry days (both 8%, Table 6). To summarize, despite the poor agreement between TRMM and OWD daily precipitation amount, 14-day total rainfall amounts and distribution (*i.e.*, frequency of wet/dry days) were in reasonable agreement with OWD, and therefore, in absence of measured rainfall, TRMM precipitation appears to be a viable option for use in crop modeling.

Given the above analysis, we conclude that (i) NASA solar radiation can be used directly for crop modeling although uncertainty can be large at locations with complex topography, (ii) given the relatively large bias in the relationship between NASA- and OWD-temperature, with sign and magnitude of bias depending upon location, NASA T_{max} and T_{min} can be used for crop modeling only after correcting the bias using OWD T_{max} and T_{min} data for each location, and (iii) daily precipitation with both GridWD sources has poor agreement with OWD daily values, but agreement with 14-day precipitation totals is much better and TRMM 14-day precipitation has better agreement with OWD 14-day precipitation than NASA 14-day precipitation, and (iv) there was reasonable agreement between number of observed dry and wet days with TRMM compared to OWD. These results supported the use of uncorrected NASA solar radiation and T_{dew}, TRMM precipitation, and location-specific corrected NASA T_{min} and T_{max} based on a few years of observed T_{max} and T_{min} for generating a long-term weather database (PWD) as the best option for input to crop simulation models, in absence of long-term daily OWD, as evaluated in Section 3.2.

3.2. Evaluation of propagated weather data based on simulated yield and its variability

Use of PWD derived from three years of OWD, as described in Section 2.2 gave median simulated yields within ±10% of yields simulated entirely with OWD at 15 of the 18 sites (Fig. 1). Even for locations with weak correlation between NASA- and OWD-T_{max} and T_{min} (*e.g.*, Embu, Melkassa, and Katumani), mean yield simulated with PWD fell within ±10% of mean yield simulated entirely with OWD. Hence, it seems like the methodology developed here was able to correct the overall temperature bias between NASA and OWD at those sites in Sub-Saharan Africa which, despite the little agreement between daily values, resulted in similar NASA- and OWD-T_{max} and T_{min} average values for the crop-growing season. In contrast, only 8 and 6 of the 18 sites exhibited simulated yields with uncorrected NASA or MarkSim-generated weather data, respectively, that were within 10% of OWD simulated yield. Simulated

Table 7
Average monthly mean error (ME) of NASA gridded weather data compared to observed weather data calculated for all available years of data for maximum and minimum temperatures (T_{max} and T_{min}, respectively) as well as the standard deviation (SD) of this average mean error for 18 sites evaluated in this study. A large standard deviation of monthly mean error is indicative of large seasonal bias (highly variable annual bias).

	T_{max} (°C)		T_{min} (°C)	
Site	ME	SD	ME	SD
Gushi	6.9	0.9	1.3	0.8
Chongqing	−5.4	0.7	−4.8	1.1
Nanning	0.9	0.6	−2.6	0.4
Dedougou	−1.4	0.8	−0.3	0.7
Gaoua	−2.5	1.0	0.3	1.9
Chapata	−2.1	0.6	1.4	1.3
Choma	0.8	1.1	4.1	2.3
Katumani	1.3	0.9	3.6	1.4
Embu	1.2	1.4	1.6	0.7
Melkassa	−4.4	1.2	1.3	1.1
North Platte	−2.4	0.7	1.8	0.7
Mead	−1.3	0.9	1.5	0.6
Dekalb	0.8	0.8	2.3	0.8
Bondville	0.0	0.9	1.8	0.9
Leipzig	−0.8	1.0	−0.8	0.6
Dusseldorf	−1.0	0.6	0.4	0.3
Oliveros	0.4	0.7	0.8	0.3
Balcarce	1.1	0.9	0.5	0.2

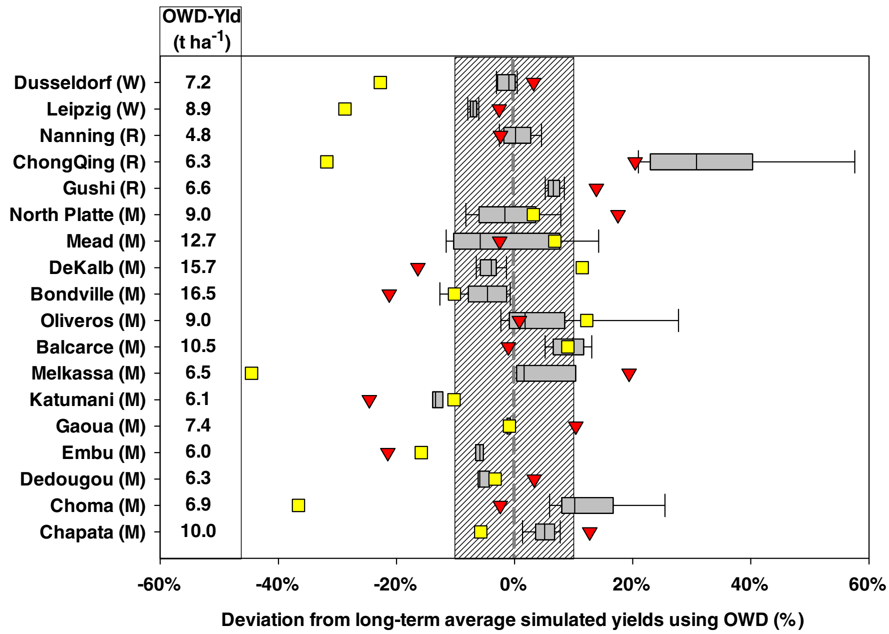

Fig. 1. Distribution of long-term average yields simulated with all possible subsets of propagated weather data (PWD, boxplots) derived from calibration with 3-year of observed weather data (OWD) and their deviation from long-term average yield simulated entirely with OWD for maize (M), rice (R), or wheat (W) at 18 locations. Yields simulated with uncorrected NASA weather data (red triangles) and MarkSim weather data (yellow squares) are also shown. Boxplots display percent differences between long-term average yields simulated entirely with OWD and yields simulated with PWD calibrated with all possible subsets of 3-year OWD series. Lower and upper boundaries for each box are the 25th and 75th percentiles. The line inside each box indicates the median. Whiskers (error bars) above and below the box indicate the 90th and 10th percentiles. Deviation of ±10% is shown as shaded background. Long-term average yields based on OWD are displayed in a table along the *Y* axis (OWD-Yld). MarkSim based yields at Gushi were too high to be shown (94% higher than OWD-based simulation). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

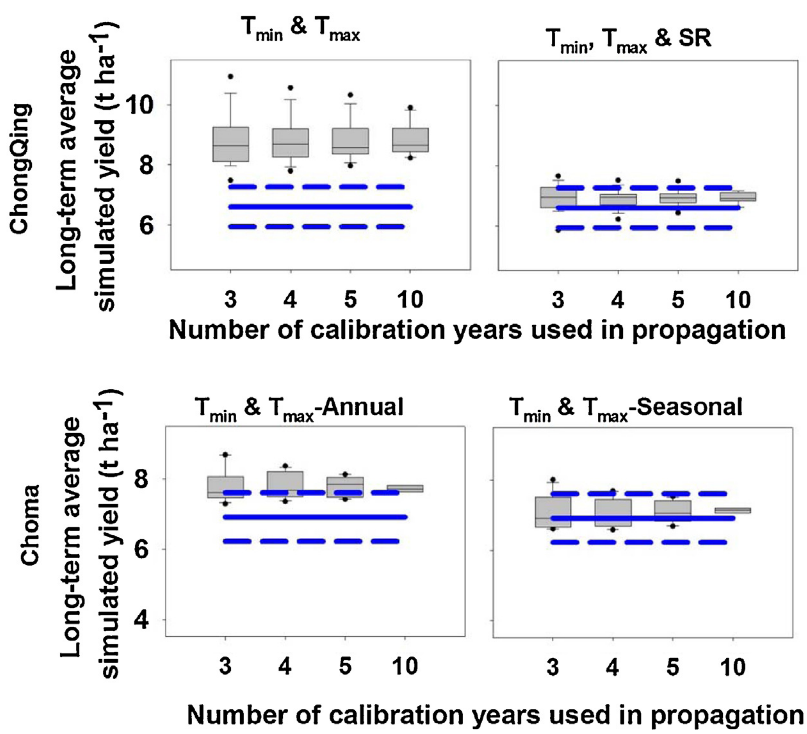

Fig. 2. Distribution of long-term average simulated yields using propagated weather data (PWD) when 3–5 and 10-year subsets of observed data (OWD) are used to correct NASA maximum and minimum temperatures (T_{max}) and (T_{min}) based on an annual calibration (left panels for both Chongquin and Choma locations) *versus* simulations in which PWD for Chongqing included a site-specific correction for solar radiation (SR, upper right panel) or a seasonally calibrated T_{min} and T_{max} for Choma (lower right panel). The box plots display the median, 10th, 25th, 75th, and 90th percentiles as vertical boxes with error bars. For reference, long-term average yields simulated using OWD (blue line) and ±10% of long term average yields simulated using OWD (dashed blue lines) are overlaid across the chart. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

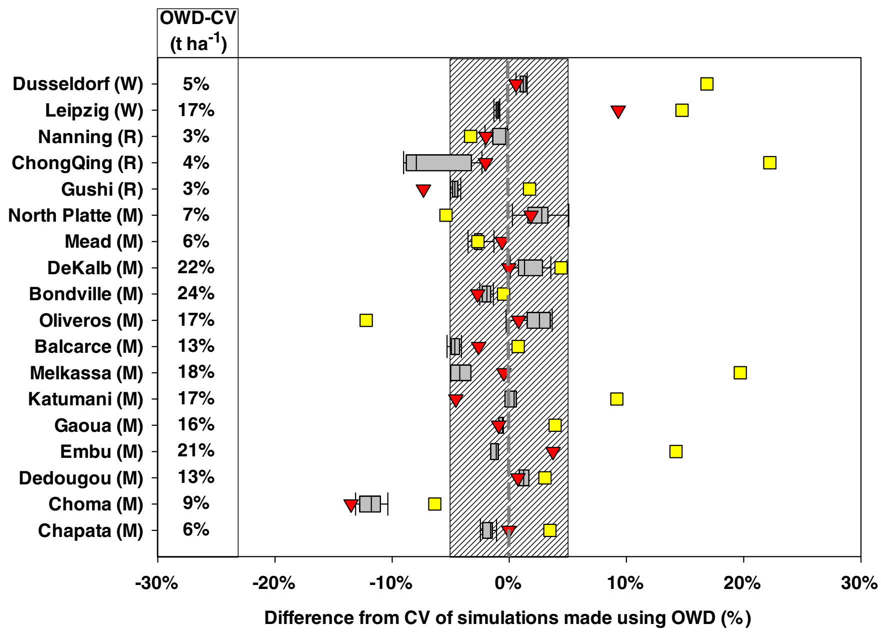

Fig. 3. Distribution of inter-annual coefficient of variation (CV) in yields simulated with all possible subsets of propagated weather data (PWD, boxplots) derived from calibration with 3-year of observed weather data (OWD) and deviation of these CVs from long-term average CV from simulations based entirely on OWD for maize (M), rice (R), or wheat (W) at 18 locations. CV of simulated yield with uncorrected NASA weather data (red triangles) and MarkSim weather data (yellow squares) are also shown. Box plots display difference between CV of OWD-based simulations and CVs of simulated yields based on PWD calibrated with all possible 3-year subsets of OWD. Lower and upper boundaries for each box are the 25th and 75th percentiles. The line inside each box indicates the median. Whiskers (error bars) above and below the box indicate the 90th and 10th percentiles. Differences of ±5% are shown as shaded background. CV of simulated yields based on OWD are displayed in a table along the *Y* axis (OWD-CV). MarkSim based yields at Nanning are too high to be shown (94% larger than OWD-based simulation). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

long-term average yields using uncorrected NASA data combined with TRMM precipitation were very similar to those with uncorrected NASA weather data that included NASA precipitation (Fig. S1). The bias between yields simulated with uncorrected NASA or MarkSim weather data and OWD-simulated yields was inconsistent across locations. Use of uncorrected NASA data led to mean simulated yields outside the ±10% OWD-yield band in 33% (above) and 22% (below) of the cases (Fig. 1). MarkSim-simulated yields fell outside the ±10% OWD-yield band in 22% (above) and 44% (below) of the cases.

Results for two sites at which a majority of yields simulated with PWD fell outside the ±10% OWD-yield band were further investigated to identify the cause of the discrepancy. For example, regardless of how many years were used in the calibration of NASA T_{max} and T_{min}, simulated yields with PWD at ChongQing (China) were about 34% higher than OWD-simulated yields (Fig. 2). The over-estimation was caused by the difference in solar radiation between NASA and OWD, which, in turn was associated with heterogeneous topography at this site. Similar discrepancies in solar radiation have been found at locations with complex topography in previous studies that evaluated use of NASA weather data for simulation of crop yields (Bai et al., 2010; White et al., 2008b; Van Wart et al., 2013b). At Choma, a site with mean PWD-simulated yields 13% higher than OWD yields, the higher simulated yields with PWD were associated with seasonal differences in the magnitude of the bias between NASA and OWD T_{max} and T_{min} (Table 7). Hence, calibration of NASA daily temperatures based on regression with the observed short-term weather data did not provide a consistent correction for propagated T_{max} and T_{min} for this site.

PWD-simulated yields at these two locations could be substantially improved, however, by addressing the location-specific discrepancies between NASA and OWD weather databases (Fig. 2). For ChongQing, calibrating NASA solar radiation, using the same calibration method as used to correct NASA T_{min} and T_{max}, resulted in PWD-simulated yields in close agreement with OWD-simulated yields. Similarly, PWD-simulated yields at Choma were much more consistent with OWD yields when NASA T_{min} and T_{max} were calibrated separately for four subsets of three consecutive months, which accounts for the seasonal difference in the bias between NASA and OWD T_{min} and T_{max}. Thus, for both sites, a location-specific calibration of the biased weather variable, solar radiation at ChongQing and temperature at Choma, resulted in mean PWD-simulated yield and 75% of the simulated yield distribution within the ±10% OWD-yield band.

Coefficient of variation of PWD-simulated yields was remarkably similar to the degree of variation observed in OWD yields. In 16 of 18 sites, the distribution of CVs in PWD yields were within ±5% of the CV calculated for OWD yields (Fig. 3). In contrast, yields simulated with NASA- or MarkSim weather data had CVs within the ±5% CV band of OWD yields in 15 and 9 sites, respectively. While simulated yields using PWD had similar long-term yields and CVs compared with yields simulated entirely with OWD, simulation of yields for individual years was more uncertain across sites and years when compared to simulated yields with OWD for the same year (Fig. S2). Therefore, PWD generated using the method described in this paper is considerably more robust at simulating long-term average yields than the yield of a single year.

4. Discussion

GridWD or GenWD are typically used to simulate yields in studies that evaluate crop performance at locations without long-term OWD (Table 1). At issue is the accuracy and precision of such estimates and whether it is possible to improve the methods used to derive long-term GenWD. To that end, we present an alternative method to propagate long-term daily weather data based on solar radiation and T_{dew} from the NASA gridded weather database, precipitation from TRMM rainfall, and calibration of NASA T_{max}

and T_{min} using three years of observed data at a given location. Unlike some of the more sophisticated GenWD, which may require a decade or more of OWD for calibration (Baigorria and Jones, 2010), the new approach developed herein requires only 3 years of observed temperature data and thus may be useful for locations with short-term weather datasets (*e.g.*, crop breeding trials or agronomy experiment stations in developing countries). Whereas daily temperature data are often measured at such locations, instrumentation to measure solar radiation is rare and there can be large gaps of missing data in recorded daily rainfall.

Simulated yields of the major cereals across a wide range of environments using PWD, following the described protocol, clearly outperformed NASA-GridWD or MarkSim-GenWD, relative to agreement with simulated yields using OWD. comparable to those simulated using OWD. Overall, PWD-based simulations were within ±10% of OWD-based long-term average yields at 78% of all sites *versus* only 44% and 33% of the sites using GWS and GenWD, respectively, regardless of whether 3, 4, 5, or 10 years of temperature data were used for location-specific temperature calibration. Hence, 3 years of observed temperature data appear to be sufficient for deriving a robust PWD set. We conclude, therefore, that creation of PWD, as performed in this study, provides a reliable and superior alternative for crop simulation to use of GridWD such as NASA (evaluated in this study) or the MarkSim weather generator (GenWD) for locations where long-term OWD are not available. It is also notable that the PWD as described herein are likely to outperform other GridWD such as the National Center for Environmental Prediction and Department of Energy's reanalysis II (NCEP/DOE, Kanamitsu et al., 2002) or the Climate Research Unit's high-resolution gridded dataset time series 3.1 (CRU, New et al., 2002) based on previous comparisons with NASA and OWD data in simulating long-term crop yields and their variability (Van Wart et al., 2013b).

While PWD-based simulations captured inter-annual variation and long-term average yields quite well, they are sometimes not reliable for accurate simulation of yield in a specific year. PWD are also subjected to bias in those variables taken directly from GridWD without calibration such as TRMM precipitation and NASA solar radiation and T_{dew}. Hence, whenever these variables have poor agreement with ground observations, there will be large uncertainty in the PWD-simulated yields. Even in these cases, however, results of our study suggest that simulations based on PWD are in better agreement with simulated yields with OWD than simulations based on the other sources of weather data evaluated in this study. For some locations, the reliability of PWD can be further improved by using seasonal calibration of GridWD temperature rather than an annual calibration as used in this study.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agrformet.2015.02.020.

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