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Increase in irrigated wheat yield in north-west Mexico from 1960 to 2019: Unravelling the negative relationship to minimum temperature

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ABSTRACT

This in-depth analysis of the rise in farm yield (FY) of irrigated wheat in the Yaqui Valley of north-west Mexico, from around 2 to 7 t/ha between 1960 and 2019, begins by highlighting a weather component overlooked in modelling and other thinking about wheat and climate change, namely the dominant role of natural annual variation in minimum temperature (Tmin). Year to year fluctuations around the increasing yield trend were substantial (st.dev. 591 kg/ha) and were highly correlated negatively with annual fluctuations in the average Tmin January to March (Tmin J-M) which ranged from 5.0 to 11.5 ^{o}C in this period lasting from mid tillering to early-mid grain fill. Dividing the 60-year period into three consecutive 20-year periods and using multiple linear regression improved the accuracy of estimates of FY as a linear function of time in each period (responding inter alia to better technology including breeding and agronomy), with slopes of 4.5%, 0.6%, and 1.8% p.a. for 1960–79, 1980–99, and 2000–19, respectively. Tmin J-M coefficients were −218, −413, −406 kg/ha/^{o}C, or −5.9, −8.1, −6.6%/^{o}C, respectively, with R^2 always close to 0.9. Combining results, the FY response to Tmin J-M was close to −7%/^{o}C, such that over the 60-year period the Tmin J-M increase of 1.0 ^{o}C contributed a 7% reduction in FY at constant CO2. The improved estimate of FY slopes with respect to time revealed novel variation across the 60 year period to be dissected in a following paper. Annual fluctuations in Tmax J-M were not correlated with variation in Tmin J-M nor with variation in FY. Crop simulation modelling of potential yield (PY) corroborated the negative effect of increased Tmin J-M on yield and suggested that increased Tmin J-M primarily decreased days to anthesis, biomass and number of grains (/m2). Measurements retrieved from long term well-managed experiments in the Valley under constant agronomy and cultivars confirmed all the above predicted responses to Tmin J-M. Our results align with the few published studies increasing crop night temperature in the critical period of around 30 days up to the end of anthesis when grains/m^2, and hence yield, was inversely related to rate of development. In the Yaqui Valley this was strongly associated with Tmin variation. This phenomenon, and the roles of Tmax and solar radiation (Rs) variation, are discussed in detail.

1. Introduction

Crop yield progress since 1960 has enabled the world to lift per capita grain production notwithstanding the rapid rise in population, thereby reducing the real price of staple food grains and limiting the increase in crop area. Although the rate of population increase has slowed to almost 1.0% p.a. (2021), a greater rate of yield progress than today's 1.4% (2002–16, Fischer, 2020) is needed over the next 20 years, to alleviate serious undernutrition in the remaining 8% of world population, to service increased per capita demand due to rising per capita income in poorer countries, and to preserve land for environmental purposes.

Irrigated wheat in the Yaqui Valley of northwest Mexico, on average occupying about 140,000 ha, is a vital indicator of technological

Abbreviations: FY, average farm yield (kg/ha) for Cajeme District in Yaqui Valley; PY, potential yield for the region; GN, grains/m^2; Tmax daily maximum temperature, Tmin daily minimum temperature; Tmean, (Tmax + Tmin)/2; Rs, daily solar radiation (MJ/m^2); Δ, value in year n + 1 minus that in year n.

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progress. This is because wheat is a major staple in our food system, and the Yaqui Valley demonstrates what science, modern technology and responsive farmers can deliver in an environment representative of much of the developing world's wheat lands, producing about 40% of the world's wheat (megaenvironment 1, latitude 25^o to 35^o, irrigated, see Fischer et al., 2014). Moreover, since the late 1940s the region has been the principal location of spring wheat breeding and other research efforts of the International Maize and Wheat Improvement Center (CIMMYT), and its predecessors. CIMMYT has been an important source of improved germplasm for the developing world since the 1960s. The Yaqui Valley, the cradle of the Green Revolution in wheat, has seen average wheat yield, hereafter defined as farm yield (FY),[1] rise from around 2 t/ha in 1960 to 7 t/ha today. Finally, in the Valley CIMMYT has conducted a great deal of agronomic and crop physiological research, which should now lead to a thorough understanding of wheat yield determination in this important environment. Thus, our paper specifically explores the effect of annual weather variation[2] and its overall trend on FY fluctuations and trends, to reveal more accurately the weather-corrected technology-driven trend, which will be disaggregated in a following paper.

Despite the use of irrigation and the semi-desert nature of the Yaqui Valley, detailed analyses reveal considerable annual (year to year) variation in FY. Wheat is sown in late November-early December and harvested in April-May. Average temperature (Tmean Nov-Apr) can vary up to 3 ^{o}C from one year to another and from early on farmers and researchers in the Valley believed that "warmer" years produced lower yields.

The effect of temperature on yield was first quantified for the region by Bell and Fischer (1994). Over the period 1968–69 to 1990–91 (hereafter we use harvest years i.e., 1969–1991), FY increased linearly at 57 kg/ha/yr for an overall increase of 25%. However, correcting for Tmean increase over these years using the Ceres wheat simulation model (v2.1) with the best cultivar and management of the time, these authors found that modelled yield (potential yield, (PY), Fischer, 2016) was closely and negatively related to Tmean November-April, decreasing about 9% per ^{o}C increase. Since Tmean November-April had steadily increased over the sample period (slope 0.053 ± 0.020 ^{o}C/yr), PY had decreased 11% due to this warming. Applying this correction, FY increase due to technology over the 23-year period would have been 32%.

A decade later, Lobell et al. (2005) revisited FY progress in the Valley, tracking its linear progress from 1988 to 2002, and again using Ceres model simulations of PY to account for any weather trend. These results were corroborated by regressing changes in FY (ΔFY) and in weather between adjacent years (first difference method), using daily averages for Jan to Apr, namely, ΔTmin, ΔTmax and ΔRs (Rs = solar radiation). Surprisingly, only the relationship between ΔFY and ΔTmin was significant,[3] revealing a slope of −525 kg/ha/^{o}C ($R^2 =$ 0.69 ***)[4] or -9.8%/^{o}C, a result confirmed by multivariate linear regression of FY against all three climate variables as independents. The slope from the first difference approach, when applied to the significant trend in Tmin over the period (−0.161 ^{o}C/y) confirmed the surprising result from the Ceres modelling: most if not all FY increase over the period was due to the decreasing Tmin. Following up over a longer study period (1980–2004) and using multiple linear regression, Lobell and Ortiz-Monasterio (2007) found that FY was again closely correlated with Tmin (slope = − 8.2%/^{o}C***) and not with Tmax, but in contrast to Lobell et al. (2005), also with Rs (5.8%/MJ/m^2/d**) and overall R^2 was 0.85***. Ceres modelled PY confirmed this, also revealing plausible associations between PY and simulated days to anthesis ($R^2 =$ 0.58 ***), grains/m^2 ($R^2 =$ 0.92 ***) and maturity biomass ($R^2 =$ 0.94 ***), but not with grain weight or harvest index. The authors concluded that the importance of Tmin for FY resulted from the negative covariance of Tmin and Rs, and not the direct effect of Tmin. Finally, Lobell and Field (2007) took the first difference approach to changes in global yields of wheat (and other crops) from 1961 to 2002. A regression with growing season ΔTmin, ΔTmax and ΔPrecipitation explained 41% of the variation in ΔFY (for barley it was 65%); the slope for ΔT was −5.5%/^{o}C and ΔTmin had a bigger negative effect than ΔTmax for wheat, but not for barley.

This paper revisits and updates the issues surrounding yield change and the yield vs Tmin relationship in the Yaqui Valley, ahead of another paper which will separate the breeding and management components of the weather-corrected technological advance. Thus, here we look at the relationship from 1960, just before semidwarf wheats first appeared, up until 2019, re-estimating the relationship of FY to Tmin over the whole 60-year period, and then in 20-year segments which permits a more accurate estimation of the linear rates of technological progress. This paper also explores the possible causes of the negative yield relationship to minimum temperature.

2. Methods

2.1. Farm yield and regional weather data bases

Wheat data for the Cajeme Irrigation District, referred to here as the Yaqui Valley, covering the period 1960–2019, were available from Mexican Government sources and are considered very reliable. It is worth noting that bread wheats dominated in the early years in the Valley, but durum wheats began to be grown in the late 1970s and dominated after the late 1990s. Their yield performance generally matched that of bread wheats of the same vintage and the two species are, with one exception (see later), not separated in the analyses of this paper.

For daily weather for the Valley (Tmin, Tmax, Rs and precipitation) the meteorological station at the main agricultural experiment station (CIANO, later renamed CENEB) was our first preference, but other nearby official stations were used for gap filling, especially before 1970.[5] The station is in the central north of the Valley, away from any urban influence and is considered representative of this flat wheat-growing area, about 50 × 100 km, close to sea level and adjacent to the Gulf of California. Daily ground-based Rs recordings began in Nov 1968, but after 1983 came from NASA satellite-based estimates which provided a continuous record from then to the present. Earlier daily Rs ground measurements were adjusted slightly to match NASA data, the adjustment from a period when the data sources overlapped.

2.2. Weather variables on which to focus

The first issue to resolve was which months gave the best fit for variation in yield versus Tmin? It had already been noted that Jan and Feb Tmin values were almost as useful as Jan to April (Ortiz Monasterio and Lobell, 2012). In addition crop physiological studies at CIANO in the 1970s clearly identified the period of approximately 30 days leading up to anthesis (at approximately mid-late Feb) had the strongest influence (through both temperature and solar radiation) on grain number (GN,

[1] In the Yaqui Valley wheat moisture content at the receival weighbridge is close to 12% (on fresh weight basis)

[2] Elsewhere often known as weather anomalies

[3] Note this slope is the effect of variation in ΔTmin plus any others weather variation associated with ΔTmin, in particular ΔRs with which variation in ΔTmin tended to be negatively and usually significantly associated (see later and Fischer, 1985; Lobell and Ortiz Monasterio, 2007).

[4] Throughout, significance probability levels of R^2 values are abbreviated ns P > 0.10, $^+$ 0.10 > P > 0.05, * 0.05 > P > 0.01, ** 0.01 > P > 0.001, ***P < 0.001 and the values are not adjusted for the number of independents which never exceeded 3.

[5] Except before 1968 when only reliable monthly temperature means were available.

/m^2), a major determinant of yield across years (Fischer, 1985), while mean temperature in Mar was identified as the main determinant of grain weight (GW, mg). Clearly grain yield was largely determined by the end of March under the recommended late Nov to early Dec sowing dates. For these reasons, temperature means for individual months and groups of months were tested to see if the earlier reliance on a linear relationship between FY and Jan-Apr means was always the best fit. Means of individual months from Jan to Apr, as well as of pairs of months were inferior to the Jan to Mar mean, which gave a similar fit as Jan to Apr mean temperatures. Adding monthly solar radiation (Rs) did not improve the fit. For reasons of parsimony and alignment with physiological understanding (e.g., grain yield and even GW are largely determined well before Apr with normal sowing dates) it was decided to focus attention here on weather in the Jan to Mar period in this study, abbreviated as Tmin J-M, Tmax J-M, Tmean J-M and Rs J-M.

2.3. Crop simulation modelling

To obtain an independent and physiologically-sound measure of weather effects, we conducted simulations using the Agricultural Production sIMulation (APSIM, Holzworth et al., 2014). We used the wheat module version 7.10 R3008, described in detail in Zheng et al. (2015). The ability of this model, hereafter known as APSIM, to simulate wheat anthesis time and grain yield has been soundly validated in numerous studies of wheat, including irrigated wheat (e.g., Asseng et al., 2004). We based the simulations on the recent popular wheat cultivars Borlaug100 2014 (bread wheat) and Cirno 2008 (durum wheat), using the following variety parameters (*vern_sens* = 1.5; *photop_sens* = 3.4; *tt_floral_initiation* = 650 ^{o}Cd; *grains_per_gram_stem* = 30; *max_grain_size* = 0.060 g). Simulations assumed rate of development before flowering to only be constrained if Tmean exceeded 26 ^{o}C (which never happened) and assumed no limitation by soil constraints, mineral nutrition, water supply or pests. Thus, the model was initialised 20 days before sowing with a full soil water profile (190 mm) and mineral N content of 20 kg N/ha. Four post sowing irrigations supplied 350 mm and split N applications 328 kg N/ha as urea. This was assumed to simulate PY, in this case PY with the today's best cultivars and agronomy. No adjustment was made for changing CO_2 levels over time (the default value of 350 ppm, the level around 1990, was used throughout.

The model was calibrated against the average grain yield (PY) and days to anthesis of the above two cultivars in the fully irrigated optimally-managed treatments of Honsdorf et al. (2018) over the five years 2013–2017 which determined the cultivar parameters above. The mean observed PY was 7866 kg/ha and the average deviations (simulated less observed) were small: for PY (−228 kg/ha, (standard deviation 336 kg/ha) or a 3% underprediction. For days sowing to anthesis (mean observed value 87.4 days), the average deviation was + 2.2 days (an over prediction with a standard deviation 2.9 days). The model was subsequently validated against 8 years of observations averaged over 22 other cultivars in the same experiment. APSIM fitted annual variation in yield and days to anthesis well (respectively: R^2 = 0.747**, mean deviation +729 kg/ha; R^2 = 0.735 **, mean deviation +1.9days). The 10% overprediction of yield agrees with the difference in average vintage of the 22 cultivars (1994), some 17 years earlier than that of the two calibration cultivars (2011). APSIM was thus deemed satisfactory for our purposes which was primarily to explore the effects of weather variation on yield and especially its components. Thus PY of wheat was simulated each year from 1969 to 2019; for these simulations, wheat was sown on 5 December, the estimated average sowing date of the Valley.

2.4. Experiments measuring wheat responses to weather

Multiyear experiments with optimal agronomy and little or no change in cultivars at the Valley experiment station had the advantage of accurate measurement of PY and often of additional traits, under weather and soil conditions well representative of the Valley. Results from several such trials covering 1986–1997 and summarised in Sayre and Moreno Ramos (1997) were used for comparison with Valley FY responses. Results of a similar long running experiment (2011–2015) with additional trait measurements, reported by Honsdorf et al. (2018), could be supplemented by unpublished data from the same experiment in 2010 and again from 2016 to 2018. Thus, a set of 11 bread wheat and 11 durum wheat cultivars, representing vintages from 1966 to 2008, was common to all 8 years (one year lost due to unusual frost, see later). Plots comprised two 5 m long raised beds, with two rows 26 cm apart on each bed, separated by furrows for irrigation with 80 cm between bed centres. Again irrigation, fertiliser and weed and disease management was such as to achieve PY. Days to anthesis was recorded plus a sample of 50 random culms at maturity were processed for spike traits and harvest index, before combine harvest of the whole plot; grain weight (GW) was measured, and grain number (GN, /m^2) and final biomass were calculated. The data were averaged across all 22 cvs, and across irrigated permanent and irrigated annually-reconstructed beds, for tillage had little effect on yield (Honsdorf et al., 2018).

2.5. Analysis of wheat response to weather

Two simple methods explored FY vs. weather relationships. The first difference method, as used by Lobell et al. (2005), was appropriate for analysis of the whole 60-year period. It uses linear regression to relate ΔFY from one year to the next (absolute or relative), to changes in single weather variables between the same years; there is no control for other associated changes in weather. Long term trends appear as the predicted ΔFY intercept when annual weather change is zero and was always very small relative to ΔFY fluctuations. The second method applied separately to each of the three 20-year periods comprising the 60 years studied, involved linear or multiple linear regression between FY or PY or other crop traits, as the dependent, and time and weather variables, as independents. This was done to get an accurate estimate of the impact of technology, assumed to increase linearly with time in any 20-year period.

3. Results

3.1. Climate and weather features 1960–2019

Table 1 shows climate averages for key months of the wheat cycle over the 60-year study period. Emphasis here is on Tmin J-M, which varied considerably, ranging from 5.0 ^{o}C (1964) to 11.5 ^{o}C (2015) with a standard deviation of 1.32 ^{o}C, and showing a tendency to cycle through cool and warm periods (Fig. 1). Also, Tmin J-M trended weakly upwards (Fig. 1, slope 0.0164 ± 0.0098 ^{o}C/yr, R^2 = 0.0464^{+}) leading to an increase of 1.0 ^{o}C over the 60-year period. Tmax J-M exhibited a smaller range (23.5 ^{o}C (1973) to 28.2 ^{o}C (1996)) and standard deviation (0.99 ^{o}C), but a stronger increase (slope = 0.0287 ± 0.0066 ^{o}C/yr, R^2 = 0.248 ***, or + 1.72 ^{o}C in 60 years). As expected, Tmean J-M was intermediate, ranging from 14.7 (1964) to 19.3 (2015) ^{o}C, also increasing strongly (slope 0.0224 ± 0.0063 ^{o}C/yr, R^2 = 0. 165 ***, or + 1.34 ^{o}C overall).

The large range in Tmin J-M is partly related to patterns of persistence of low or high minimum temperatures across several months, for example a significant correlation between March and February Tmin (R^2 = 0.293 ***, slope 0.43 ± 0.087 ^{o}C/^{o}C). There was also significant persistence in Tmin J-M from one year to the next (R^2 = 0.262 ***), especially after 1990 (Fig. 1). There was no such pattern in maximum temperatures. However, annual Tmax J-M was significantly but weakly related to Tmin J-M (R^2 = 0.123 **, slope 0.267 ± 0.094 ^{o}C/^{o}C). Mean monthly Tmax and Tmin were weakly correlated for February, March, and April (R^2 around 0.20 ***, slope around 0.3 ^{o}C/^{o}C).

Temperature extremes could be important for understanding FY. Frost in Dec or Jan (Table 1, lowest value −4.3 ^{o}C) was generally too

Table 1
Average values of key climate variables for the months of the wheat season from Nov 1959 to April 2019 in the Yaqui Valley (CIANO/CENEB, lat 27 N, 109°W, 40 masl).

Month	Tmax °C	Tmin °C	Tmean °C	Tmin < 2 °C days	Solar Radn.[a] $MJ/m^2/d$	Total precip. mm	Monthly rainfall > 100 mm # years
November	29.5	12.4	20.9	0	15.8	9.4	1
December	24.9	8.9	16.9	0.28	13.6	17.4	1
January	24.2	7.5	15.9	0.46	14.5	16.7	2
February	25.3	8.1	16.7	0.30	18.0	9.6	0
March	27.5	9.2	18.3	0.04	22.6	4.0	0
April	31.1	11.3	21.2	0	26.4	1.9	0
Mean J-M	25.7	8.25	17.0		18.4		

[a] 1968–2019 only.

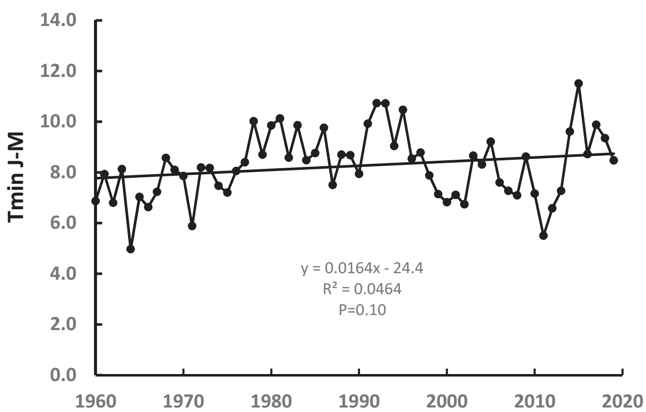

Fig. 1. Annual variability in mean January to March Tmin (Tmin J-M) over a 60-year period for the Yaqui Valley.

early to damage the yield of wheat sown at the recommended data. However, from 3 to 7 February 2011, on three consecutive days temperatures fell below zero (coldest −2.2 °C), leading to reports of widespread damage to wheat, which was generally in early boot to heading stage. The extensive review of Porter and Gawith (1999) suggests that Tmax values greater than 30–32 °C might damage wheat around flowering (at least in controlled environment studies). In the Yaqui Valley canopy temperature of irrigated wheat is normally several degrees below air temperature due to transpiration cooling (see later). Therefore Tmax values equal to or greater than 34 °C were chosen here to explore potentially damaging heat events. From the daily temperature records (1969–2019), on average one such event occurred in March every two years, but 5 events in April every year, with no tendency for an increase in frequency over the study period. There were only 3 occurrences of Tmax exceeding 36 °C in the Jan to Mar 1969–2019 dataset, all in late March and 36.7 °C the highest. The low frequency of extreme temperature events undoubtedly reflects the moderating effect of the Valley actually being a coastal plain running along the Gulf of California.

Monthly mean solar radiation (Rs) did not change significantly over the period 1969–2019, nor did mean Rs J-M. However, there was annual variability in the latter of the order of 20% across years (range 16.8–20.0 MJ/m2/d). In February, mean Rs varied by 40% (range 14.4–20.4 $MJ/m^2/d$).[6] A moderately strong negative relationship between monthly mean Rs and Tmin was seen for each month from Jan to Apr and there was a significant correlation between Rs J-M and Tmin J-M (slope– 0.352 ± 0.072 MJ/m2/d/°C; $R^2 = 0.327$ ***). Monthly Rs was generally positively correlated with Tmax, but it was not always significant, and not significant for the J-M means. February is the most important month for yield determination and periods of heavy cloud then can reduce yield as in 1973 experiments when the three-day mean Rs (19–21 February fell to 6 $MJ/m^2/d$; Fischer, 1985). An equally cloudy event occurred on 2–4 February 2002. These unusual patterns no doubt reflect, in this semi-desert coastal environment, the variation between years with persistent cloudiness (and higher Tmin), at one extreme, and cloudless years with lower Tmin values at the other.

Average annual rainfall was 317 mm (1979–2014), but rain during the wheat season (November to April) averaged 60.3 mm and showed no time trend across the 60 years. However, there is notable annual variability of winter rain in this semi-arid environment. Wet winters bring rain to the mountainous region immediately east of the Yaqui Valley filling the irrigation reservoirs (Schoups et al., 2012). The frequency of Nov to April totals above 100 mm decreased from 5 years in 1960–79 and in 1980–99, to only 2 in 2000–19, causing a general decline in dam inflows. For 8 consecutive years winter rains were below 100 mm leading to peak scarcity of canal water in 2004 and more reliance on pumped aquifer water for irrigation. Also, winter rain on the crop land around sowing time can be problematic. A monthly total > 100 mm was recorded in Nov 1974 (117 mm) and Dec 1959 (106 mm), and Nov-Dec rainfall in 1967, 1982 and 1994 exceeded 100 mm. Nov and Dec rains can delay sowing and/or affect emergence, as suggested in the analysis of Bell et al. (1995). Heavy Jan rain (152 mm in 1992 and 147 mm in 2004) was fortunately too late to reduce crop emergence,

3.2. Farm yield (FY) and weather effects 1960–2019

Wheat yield increased more than three-fold over the 60-year study period (Fig. 2). The fit of a third order polynomial to FY change is reasonably close with all coefficients highly significant, and significantly better overall than a linear model; it serves here simply to highlight an apparent slowdown in FY progress during the middle of the 60-year period. Annual wheat area averaged 137,000 ha, but fluctuations were large, with a high of 196,000 ha in 2015 and a notable collapse to only

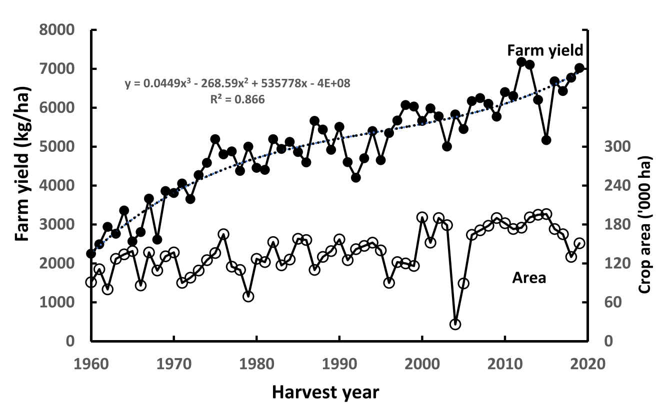

Fig. 2. Variation in Yaqui Valley farm yield (closed) and sown area (open) of irrigated wheat for all years, 1960–2019. Dotted line is a third order polynomial fitted to the yield data (FY in 1977 was adjusted up 750 kg/ha to account for leaf rust).

[6] Mean February clear sky Rs for the Yaqui Valley is estimated at 19.8 $MJ/m^2/d$ (assumed visibility 50 km, dew point 10 °C, following Iqbal (1983).

26,000 ha in 2004 due to the shortage of canal water (Fig. 2). Fluctuations in FY and area were not related.

There were no a priori reasons for altering or excluding FY data of any year, with two exceptions. The first exception was the year 1977 when it was estimated that a leaf rust epidemic caused losses amounting to 750 kg/ha (Dubin and Torres, 1981); this amount was added to the 1977 FY as a valid adjustment for all subsequent analyses of FY. The second exception was the earlier-mentioned 2011 February frosts which had a notable effect on FY; without a reliable estimate of the yield loss, this year was excluded from further analyses, although later a reasonably-sound estimate of the frost damage is made.

The first difference method permits a ready look at the relationship between the year-to-year FY fluctuations in Fig. 2 and fluctuations in weather variables, such as Tmin J-M seen in Fig. 1. Thus the ΔFY vs ΔTmin J-M showed a strong negative relationship over the 60-year period (slope $= -348 \pm 39$ kg/ha/°C, $R^2 = 0.589$ ***) and normally distributed residuals. The relationships of ΔFY to ΔTmin of individual months were always weaker, but it is noteworthy that ΔTmin Feb gave the best fit ($R^2 = 0.415$ ***). For ΔTmax J-M the relationship to ΔFY was also negative but very weak and non-significant ($R^2 = 0.042$, $P > 0.10$); ΔTmean J-M was intermediate in fit (slope -367 ± 62 kg/ha/°C, $R^2 = 0.409$ ***).

Applying the same method to the percentage difference in FY year to year (relative to the average of the two adjacent years), possibly a better measure when FY was trending so strongly upwards, gave another strong relationship to Δ J-M Tmin ($R^2 = 0.510$ ***) and a FY change of $-7.35\% \pm 0.96\%$ /°C, while the relationship to ΔTmax J-M remained non-significant. Finally, the values of ΔFY, ΔTmin and ΔTmax showed no trend across years. Their standard deviation (about the mean of almost zero in each case) was for ΔFY (591 kg/ha), relative ΔFY (13.4%), and ΔTmin J-M (1.30 °C). Apart from excluding 2011 because of frost damage and noting that 1968 had a lower ΔFY than predicted (673 kg/ha) and a wet Nov – Dec, there was no evidence that the other weather extremes described in Section 3.2 (e.g., Tmax > 34 °C, periods of heavy cloud in February, other years with heavy rain at sowing time) had any noticeable effect on FY deviations.

The fit of ΔFY variation to that ΔRs J-M was poor ($R^2 = 0.186^{+}$), but that to the photothermal quotient Δ(Rs J-M/Tmean J-M) was better ($R^2 = 0.585$ ***). However, these correlations were restricted to the years with Rs data (1969–2019), a period for which the ΔFY was clearly better explained by ΔTmin J-M ($R^2 = 0.724$ ***, slope -386 ± 34.7), very close to that seen for 1960–2019. The utility of ΔTmin J-M alone as the best predictor of interannual yield change, first noted by Lobell et al. (2005), is clearly vindicated, and the power of the simple first difference relationship, despite all the other factors which might influence FY, is what underpins this paper attempting to separate technology-driven trends from weather variability.

3.3. Farm yield progress and weather by 20-year periods

The long-term FY trend in Fig. 2, although slightly influenced by the Tmin J-M increase, is largely dominated by technological progress. The polynomial relationship shown, with decreasing then increasing rate of change over time, fits the data better than a linear one, but it is evident that 60 years is too long a period over which to expect one simple linear driver of progress, hence the shorter 20-year study periods adopted (1960–79, 1980–99, 2000–2019). These periods showed linear technological progress in FY, something much more accurately estimated by multiple linear regression, rather than with the first difference method.

3.3.1. FY versus time and weather 1960–1979

The 20-year period 1960–1979 encompassed the introduction and rapid adoption of semidwarf wheat varieties and much more N fertiliser ; it is not surprising that FY increased rapidly. Across this period the key weather variables were examined with the limitation that monthly Rs was only available from 1969 onwards. Tmin J-M showed a steady and a significant increase with year (0.0969 ± 0.037 °C/yr, $R^2 = 0.273$ *). There were no surprises relative to the more general relationships between weather variables mentioned earlier, although for Rs (available only from 1969), that in Feb showed a stronger negative correlation to Feb Tmin ($R^2 = 0.619$ **), with weaker relationships in Jan and Mar.

Using linear regression, FY was very strongly related to year, with a slope of 151 ± 14.0 kg/ha/yr ($R^2 = 0.859$ ***). A multiple linear regression including year and Tmin J-M enabled another estimation of the annual yield improvement ($R^2 = 0.885$ ***):

$$\text{FY (kg/ha)} = -321{,}617 + 166 \pm 15.3 \text{ x Year} - 218 \pm 82.3 \text{ x Tmin J-M} \quad (1)$$

Residuals in estimated FY appeared normal but the standard deviation was moderate at 317 kg/ha with several residuals over 500 kg/ha. In order the capture relative changes for the period, slopes in Eq. (1) were expressed relative to the mean FY[7] for 1960–1979 (3695 kg/ha), giving a very high 4.5% p.a. increase in yield due to year and 5.9%/°C decline in yield due to the negative effect of increasing Tmin J-M.

Testing of other weather variables as third terms in Eq. (1), did not provide significant improvements in this relationship (Rs data was not available for the first half of the period). Also there appeared to be no effect of extreme weather events in the 20-year period, apart again from the 626 kg/ha over prediction of 1968 FY, a crop which saw a very wet planting time (Nov -Dec precipitation > 100 mm). Following Eq. (1) but fitting without 1977, the leaf rust year, predicted a yield of 5391 kg/ha. Actual yield was 4127 kg/ha, so the predicted damage (1264 kg/ha) was greater than the estimated amount of 750 kg/ha (Dubin and Torres, 1981). Nevertheless, all modelling shown here retained a 1977 yield adjusted a priori upwards by this lower estimated loss, and retained 1968 unadjusted.

3.3.2. FY vs weather using 1980–1999

This period was one of apparent ongoing technological innovation, combined with some socioeconomic upheavals in the Valley. Monthly Tmax, Tmin, Tmean, and solar radiation (Rs) continued to show the relationships with one another reported above. However, in contrast to 1960–79, there were no significant weather trends over time, although Tmin J-M fell overall, it fluctuated notably, especially in the 1990s (Fig. 1).

Between 1980 and 1999 FY rose linearly at 46.6 ± 18.6 kg/ha/yr; the relationship was significant but not strong ($R^2 = 0.259$ *) due to the large year to year fluctuations in Tmin J-M, which ranged from 7.15 to 10.73 °C. Including it in the multiple linear relationship gave a much-improved fit ($R^2 = 0.874$ ***):

$$\text{FY (kg/ha)} = -50{,}783 + 30.0 \pm 8.1 \text{ x Year} - 413 \pm 45 \text{ x Tmin J-M} \quad (2)$$

Residuals appeared normal, with a standard deviation of only 193 kg/ha. The largest was an underprediction of 382 kg/ha in 1983; residuals bore no relation to weather extremes. This fitting procedure also provided a much more accurate estimate of the effect of year, namely a linear yield increase of 30.0 kg/ha/y. The mean FY for the period 1980–1999 was 5088 kg/ha and the yield improvement was 0.59% p.a. while the coefficient for Tmin J-M was −8.1%/°C. The contrasting slopes between 1960 and 79 and 1980–99 (Eq. (1) vs Eq. (2)) are notable, with a much greater effect of year, and weaker effect of Tmin J-M in the former period, although this latter contrast was smaller in relative terms (−5.9% vs −8.1% /°C).

Including other weather variables in Eq. (2) did not improve the relationship. For example, a special effort was made in this period to look at weather variables known to drive grain number (e.g., photothermal quotient for January and February, Fischer, 1985) and grain

[7] This denominator for calculating relative changes is used throughout the paper, as the periods themselves are the subject of interest here, not what they predict for future years.

weight (Tmean March) were examined but the R^2 values were not improved.

3.3.3. FY versus weather 2000–2019

Technological innovations were expected to continue in the final study period, which also included notable water shortages and wheat area reduction in 2004 and 2005 (Fig. 2), as well as greater socioeconomic stability and increases in real wheat prices. Weather patterns in this final 20-year period (excluding 2011 because of frost damage) were generally similar to those seen in the earlier periods. However, Tmin J-M increased significantly (0.115 ± 0.045 * C°/yr) as did Tmax (0.071 ± 0.29 *C°/yr) while Rs was unchanged and showed no relationship to Tmin J-M.

FY showed a highly significant linear increase over the 2000–2019 interval (62.1 ± 19.8 kg/ha/yr, $R^2 = 0.367$ **). Again, correcting for interannual weather fluctuations by using Tmin J-M improved the FY fit notably, with $R^2 = 0.898$ ***:

$$\text{FY (kg/ha)} = -209{,}245 + 108.9 \pm 9.65 \text{ x Year} - 406 \pm 45 \text{ x Tmin J-M} \quad (3)$$

Residuals appeared normal with a standard deviation of 193 kg/ha for FYs which ranged from 5002 to 7175 kg/ha. The largest residual was an over prediction in 2008 of 364 kg/ha, but residuals again showed no relationship to the noted weather extremes. However, the largest FY underprediction −296 kg/ha or −5.4%) occurred in 2004, the year with the lowest wheat area in 60 years due to lack of canal water (see Fig. 2), suggesting the best soils/managers may have predominated, but noting crop water supply was aided by heavy January rain (147 mm). The linear annual yield increase of 109 kg/ha/yr was significantly higher than the previous 20-year period (30.0 kg/ha/yr), something not so evident in Fig. 2 since it was partly dampened by Tmin increase. Considering the mean yield for the period was 6154 kg/ha (excl. 2011), the mean annual yield increase was 1.77% p.a. and the effect of Tmin J-M was a yield decrease of 6.6%/°C. Including other temperature variables in Eq. (3), such as Tmax J-M or Tmax Apr, did not improve the relationship. Including Rs J-M increased R^2 to 0.914 with a weakly significant coefficient (110 kg/ha/MJ/m^2, P = 0.10).

Interestingly, Eq. (3) predicted a FY of 7424 kg/ha in the year with early February frost (2011); this was 1123 kg/ha above the actual FY. This estimates that frost reduced yield about 15%. While this estimate involves extrapolating the relationship FY vs Tmin J-M to the second lowest value ever seen (5.51 °C), this is probably sound. Earlier the lowest value ever (4.97 °C in 1964 and without frost) predicted an FY within 2% of the actual FY using Eq. (1) derived above for 1960–1979.

3.4. APSIM-simulated potential yield (PY) change under best technology

From 1969–2019, the PY simulated using APSIM with constant variety and agronomy showed a surprisingly large range, from 6143 kg/ha (1993) to 9631 kg/ha (2010), with mean value of 8521 kg/ha, a standard deviation of 851 kg/ha, and obvious persistence of deviations from the mean (Fig. 3). Because of the large fluctuations, the apparent downwards trend in PY with year was not significant ($R^2 = 0.012$). Comparing FY in Fig. 2 to PY Fig. 3 over the final decade (2010–2019), a period for which the assumed variety and agronomy for PY modelling was presumably available to farmers, it is seen that the yield gap (PY-FY) averaged about 21% of PY, to which should be added the simulated PY underestimate of 3% of observed PY when calibrated against the latest two cultivars, making a gap of 24% of PY, a gap which is quite low by most standards (e.g., Fischer, 2020).

After excluding 2011 for frost, the relevance of the annual PY fluctuations (Fig. 3) to fluctuations in FY (Fig. 2) is seen using again the first difference method, when ΔFY values are compared to ΔPY ones (slope 0.4, $R^2 = 0.400$ ***). The slope indicates that the fluctuations in FY were about 40% the magnitude of fluctuations in PY. PY was closely and inversely associated with Tmin J-M (slope -520 ± 55 kg/ha/°C or

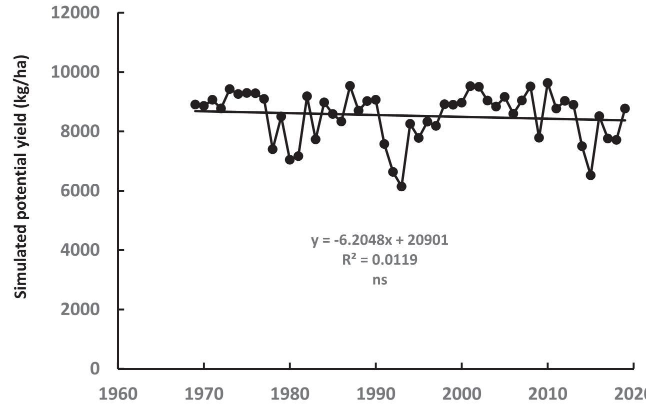

Fig. 3. APSIM simulated PY using 5 Dec sowing, and latest agronomy and cultivars across all years, 1969–2019.

−6.1%/°C, $R^2 = 0.649$ ***), while again there was a non-significant negative relationship between PY and Tmax J-M ($R^2 = 0.118$ ns). There were also weaker but highly significant PY relationships each month, with Tmin (negative) and Rs (positive). PY relationships with a photothermal quotient (simply Rs/Tmin) were never better than those with Tmin alone. Clearly the APSIM PY results respond to weather in the same way as FY ones did, with a remarkable sensitivity to variation in Tmin and the lack of sensitivity to variation in Tmax.

APSIM estimates other crop traits besides PY. Thus, average anthesis date was March 8, with crops in all years flowering in the first half of March; average maturity date April 14. PY variation was closely related days to anthesis ($R^2 = 0.566$ ***, slope $= 140 \pm 17.5$ kg/ha/d), to GN ($R^2 = 0.765$ ***) and to maturity biomass ($R^2 = 0.915$ ***), but not significantly related to harvest index or grain weight. Days to anthesis in turn was most closely related to mean temperature J-M ($R^2 = 0.814$ ***, slope −4.44 d/°C,), with a somewhat stronger influence from Tmin J-M ($R^2 = 0.687$ ***, slope = − 2.88 d/°C) than from Tmax ($R^2 = 0.326$ ***, slope = −2.54 d/°C).

3.5. Response of measured PY and other traits to Tmin

Sayre and Moreno (1997) showed that over 12 years (1986–1997), their annual average trial PY values in the experiment station were on average 44% higher than FY values but correlated with them ($R^2 = 0.486$ *). Also their trial yields correlated negatively with Tmin J-M (slope −500 kg/ha/°C or −6.9%/°C, $R^2 = 0.320^{+}$), a sensitivity to Tmin J-M similar to that of FY for this particular time period (−8.0%/°C, $R^2 = 0.762$ ***). With the Honsdorf data (mean of 22 varieties), PY across 2010–2018 (excluding 2011) ranged from 5892 to 8243 kg/ha, averaging 11% above FY in that period, and it also correlated closely with annual FY fluctuations ($R^2 = 0.630$ *). It can be safely concluded that well managed experiments aimed at PY are responding to the same weather factors driving annual FY fluctuations and provide a more accurate yield measure with which to investigate these factors.

Thus, in the Honsdorf dataset PY was closely correlated to Tmin J-M (slope -492 ± 35 kg/ha/°C or −6.8%/°C, $R^2 = 0.970$ ***). Yield was also related to Tmax J-M ($R^2 = 0.561$ *) but in a multiple linear regression adding Tmax J-M, explained no more yield variation than Tmin J-M alone. The other crop traits measured in the Honsdorf dataset indicate that annual PY variation was related positively to days from sowing to anthesis (slope 98.7 ± 31.4 kg/ha/d, $R^2 = 0.624$ *), to GN ($R^2 = 0.880$ **) and to biomass ($R^2 = 0.936$ ***), but not to harvest index or grain weight. Days to anthesis was closely related to Tmin J-M (slope -3.34 ± 0.89 d/°C, $R^2 = 0.704$ **) but not to Tmax J-M ($R^2 = 0.278$ ns).

A surprising result from the Honsdorf data was that durum wheats (11 of the 22 varieties tested) exhibited a significantly ($p < 0.01$) greater yield sensitivity to Tmin J-M (slope -579 ± 35 kg/ha/°C, $R^2 = 0.978$ **) than bread wheats (slope -403 ± 53 kg/ha/°C), $R^2 = 0.906$ **, despite similar mean yields (7422 vs 7031 kg/ha). Durum wheats were clearly superior in three cooler years, but not different in the warmest one (Fig. 4); however, this intriguing difference is not pursued further here.

4. Discussion

4.1. Accounting for variation in Tmin to more accurately estimate the technology trend in yield

FY responses to Tmin J-M were similar across the three study periods (Table 2) and on average similar to the first difference results (they are discussed below). Correcting for this influence more accurately estimated the annual FY increase in the three separate periods (summarised in Table 2). The differences in slope of the relationships are normally attributed to changes in technology, and were highly significantly different from each other. Moreover, they contrast with the uncorrected slopes (last column Table 2) because Tmin trends were removed, having an especially large effect on the FY slope for 2000–2019. They confirm what was suggested by Fig. 2, namely that there was a marked slowdown in yield progress during the 1980s and 1990s, and then a significant recovery. This slowdown has not been previously reported, and technological progress will be dissected in a following paper. It suffices here to emphasize that correcting for weather and climate trends revealed the underlying technological component of yield change, as pointed out in Bell and Fischer (1995). In a similar example: Hochman et al. (2017) used APSIM to estimate that the water-limited PY of wheat in Australia declined by 26% from 1990 to 2015 due to climate trends. Over that period actual FY was stagnant, indicating significant technology-driven closing of the yield gap between FY and PY.

4.2. The extent and significance of the sensitivity of FY to Tmin

Our results on annual yield variability in the Yaqui Valley extend those of Lobell et al. (2005) and Lobell and Ortiz-Monasterio (2007) from 1980−2004 to a 60-year period (1960–2019), confirming the high sensitivity of FY to variation in Tmin J-M, and the absence of sensitivity to Tmax J-M which will be discussed in 4.3. The average sensitivity to Tmin J-M in Table 2 was –346 kg/ha/°C, but since this slope clearly steepened as yield increased, it is more appropriately expressed as the average relative change −6.9%/°C. These average slopes from linear regression were close to those determined by the first difference method across the 60 year period (−348 kg/ha/°C and −7.6%/°C), and validate the latter simpler method. We conclude that wheat yield in the Yaqui Valley declined 7% for every increase of 1 °C in Tmin J-M.

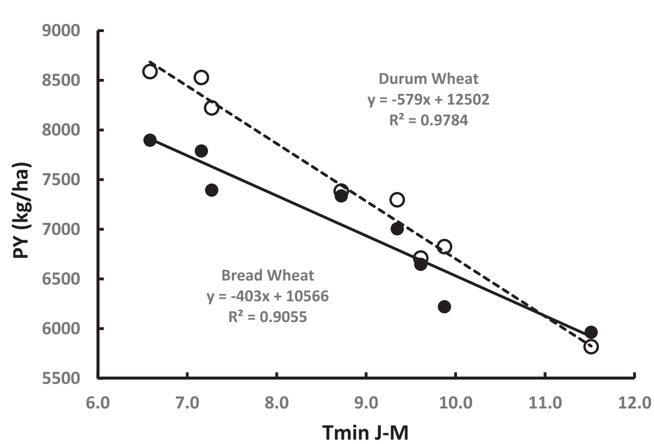

Fig. 4. Annual average potential yield (PY) of 11 bread wheat (solid symbols and line) and 11 durum wheat (open symbols, broken line) cultivars as a function of average January to March minimum temperature; 2010, 2012–2018 Source: Honsdorf et al. (2018).

The percentage of durum wheat grown varied from year to year and, favoured by resistance to a new disease (karnal bunt, *Neovossica indica*) and better markets, has trended upwards. However, including the proportion of durum wheats never significantly improved the fit of ΔFY to Δ Tmin J-M in the first difference approach, nor fit in the multiple linear regressions. Even so, the low percentage of sowings to durum wheats in 1960–1979 (3%) contrasts with the higher numbers in 1980–1999 (40%) and 2000–2019 (84%), and may have contributed somewhat to the lower sensitivity of FY to Tmin J-M reported for the first period in Table 2.

It is important to know whether the strong effect of Tmin was associated with any other weather variables. One feature of the Yaqui Valley weather, Rs variation, did have an effect on FY variation and sometimes on the Tmin J-M relationship reported here, while Tmax J-M, frost, hot spells, high precipitation events, including associated lodging, seem unlikely to have been involved (the damaging frost in 2011 has been excluded from all analyses). Between 1969 and 2019, there was a weak negative correlation between Rs J-M and Tmin J-M (slope −0.352 MJ/m2/d/°C; $R^2 = 0.312$ ***). Adding Rs J-M as an independent variable to Eqs. (1) to (3) did not improve the correlation or deliver a significant coefficient for Rs. This is possibly because the variation is Rs was small relative to that in Tmin (−1.9% on average per °C) and was captured by the Tmin variation. The positive association between Rs M-J and Tmax M-J would tend to counter any development accelerating effect of greater Tmax, but the relationship was weak and non-significant (0.174 MJ/m^2/d/°C, $R^2 = 0.049$).

The study of Lobell and Ortiz-Monasterio (2007) also looked at wheat in the nearby irrigated regions of San Luis-Mexicali (lat 32.5°N) in Mexico and Imperial Valley (lat 33°N) in USA. Curiously the empirical relationship across years of FY to temperatures (this time Jan to April) was close to zero for Tmin, but significant for Tmax (negative coefficient) in both regions, and for Rs positive in the Imperial Valley. This didn't align with the analyses from the Yaqui Valley! Possible explanations are (1) the stronger positive relationship (but generally still non-significant) between Tmin, Tmax and Rs in these locations, and (2) the choice of the Jan to April period at locations where the mean monthly temperatures were generally about 3 °C lower than the Yaqui Valley. The latter implies that January to April may not have captured the right portion of the crop cycle, or Tmin was approaching suboptimal levels for growth early in the period. For example, Ottman et al. (2012) found in nearby Arizona (lat 33° N) that artificial warming (day plus night) had no effect on wheat yield for early Dec and early Jan plantings. Perhaps surprisingly, our results may, however, concur with those of Lobell and Field (2007), in which annual change in global wheat FY was most strongly related to that in Tmin, but also to Tmax; only an average slope of −5.4%/°C was reported.

Many other studies have reported a negative influence of chronic rising Tmean on yield, generally without distinguishing the Tmin and Tmax components. Fischer et al. (2014) summarised wheat studies on chronic warming, based (1) on regression of variation in annual yield against mean temperature and (2) on crop simulations to estimate responses to raising mean temperatures by 1–2 °C above the historic record. The average yield responses to Tmean change were, − 4.1%/°C and − 7.7%/°C, respectively. Since then, a comprehensive global review of the statistical and simulation modelling approaches to yield response to temperature rise found a mean response in wheat of −6.0%/°C (Zhao et al., 2017). Considerable geographic variation is reported in this and other reviews, but unfortunately there is no analysis for any region of irrigated wheat similar to the Yaqui Valley. Even so, our numbers (−7.6% first difference, −6.9% linear regression, average −7.25%) are well within the range of the other studies. We note that the global results were based on Tmean for the whole crop season, while ours were relative to Tmin change over the key three months for yield determination. For comparison, our slope for Tmean J-M was − 7.6% by first difference,

Table 2
Summary of regressions of FY against Tmin J-M and/or year for each successive 20-year period (multiple linear regressions from Eqs. (1), (2) and (3), simple regression from text).

Period	Mean FY kg/ha	Multiple linear regression					Simple regression
		Change in FY with Tmin J-M[a]		Annual increase in FY[a]		R^2	Annual increase in FY
		kg/ha/°C	%/°C	kg/ha/yr	%/yr		kg/ha/yr
1960–1979	3695	−218 ± 82	−5.9	166 ± 15.3	4.49	0.885***	151 ± 14.0
1980–1999	5088	−413 ± 45	−8.1	30.0 ± 8.1	0.59	0.874***	46.6 ± 18.6
2000–2019	6154	−406 ± 45	−6.6	108.9 ± 9.7	1.77	0.898***	62.1 ± 19.8

[a] Relative changes expressed as a proportion of the mean FY for the period.

and 8.2% by linear regression, in reasonable agreement with world studies. One such study (Bapuji Rao et al., 2015) examined Tmax and Tmin (Nov to Mar) across all 215 wheat growing districts of India for the period 1980–2011, but without consideration of the substantial change in wheat climate across the vaste wheat belt. Nevertheless, in half of the districts ΔFY was significantly and equally related to ΔTmin and ΔTmax, with a mean slope of about −200 kg/ha/°C of seasonal temperature, or about −7%/°C. Irrigated wheat districts in NW India match the Yaqui Valley reasonably well climatically, but were not distinguished in the analysis. However, revisiting one analysis of FY progress 1990–2011 in the Indian Punjab (Fischer et al., 2014), all FY relationships seen here in the Yaqui Valley were confirmed: FY was correlated in a multiple regression with year and with Tmin (latter slope −195 ± 48 kg/ha/°C, or −4.7%/°C, $R^2 = 0.779$), and not correlated with Tmax or Rs, even though Tmin and Tmax were strongly positively related ($R^2 = 0.473$).[8]

Our results pointing to a major effect of Tmin and none of Tmax may therefore not be just confined to natural variation in semidesert coastal environments like the Yaqui Valley, where annual anomalies in Tmin and Tmax are uncorrelated and extreme minimum (< 0°) and maximum (> 34° C) temperatures uncommon. The results are also supported by the Lobell and Field (2007) analysis of global wheat yield variation in that negative correlations with Tmin were strong but those with Tmax less so. Generally, at higher latitudes Tmin and Tmax fluctuations are more likely to be positively correlated, and more difficult to unravel. From our results, it seems highly advisable for a better understanding of temperature change and wheat yield that this be attempted.

Finally, across the 60-year period temperatures have increased in the Yaqui Valley (Tmin J-M up 1.0 °C and Tmax J-M up 1.7 °C). Increases are in line with much of the world, except that elsewhere the rate of Tmin increase has generally exceeded that of Tmax (Easterling et al., 1997). This does not alter the fact that warming, by raising Tmin 1.0 °C, can be estimated from the empirical yield vs Tmin slope to have reduced yield about 7%. Applying our sensitivity figures to the Tmean J-M increase over the period (1.34 °C) would deliver a somewhat larger but less accurate estimated reduction, while the general decline in APSIM simulated PY over time was not significant due to its large annual fluctuations (Fig. 3). Also, it should be noted that our estimated FY and PY responses to temperature were not confounded by CO_2 change. For FY this was contained in the intercept with first difference analysis and in the linear trend with linear regression, and PY was simulated at constant CO_2. Over the 60-year period CO_2 has risen 26%, which other things equal is likely to have lifted yield by about 10% (elasticity of 0.4 calculated from Tubiello et al., 2007), somewhat more than balancing the negative effect of warming. The Yaqui Valley may be an exception in this respect, for example its warming rate was about half the rate mentioned above for wheat districts at a similar latitude in India (Bapuji Rao et al., 2015).

4.3. Effect of minimum and maximum temperatures on days to anthesis and other traits

The trait measurements from the Honsdorf data clearly confirmed the relationships seen in the results with the APSIM modelling of PY from 1969 to 2019 with one exception. Simulated days to anthesis (2010–2018) was highly significantly related to Jan to Mar Tmin, Tmax and Tmean (R^2 of 0.851 **, 0.753 ** and 0.869 ***, respectively) whereas for measured days to anthesis the respective correlations were (0.704 **, 0.278 ns and 0.574 *). The simulated relationships, of course, reflect the day degree sum driving phenology in APSIM with no curbing of day degree accumulation coming from high Tmax values (see 2.3). The measurements suggest that the phenology parameters used in APSIM (Section 2.3) do not fully capture the response of the cultivar to environmental variables.

Notwithstanding this difference in fit of days to anthesis, the simulated and measured results strongly support the idea that the major influence of annual Tmin J-M variation arose before and/or at anthesis with higher Tmin causing faster development and hence less crop and spike growth until then, leading to lower grain number (/m2, GN), and ultimately less yield and biomass. Measured PY was significantly related to days sowing to anthesis (slope of −98.7 ± 31.4 kg/ha/d, $R^2 = 0.623$ *).[9] These relationships are likely reinforced by two Rs effects. As mentioned there was slightly less solar Rs in warmer Tmin years, amounting to a decrease in Rs of 1.9%/°C increase in Tmin J-M. Secondly decreased Rs is to be expected on average from the “displacement effect”, from the earlier occurrence of any critical preanthesis period (see later) the more anthesis is advanced by higher Tmin: on average Rs increases 0.84%/d in February (Table 1). The response of days to anthesis to Tmin J-M from Honsdorf (−2.94 d/°C) would have amounted to 2.5% (0.84% x 2.94) less Rs at anthesis per °C increase in Tmin. Together these two effects add up to 4.5% less Rs per 1 °C increase in Tmin, or more than half the 6.9%/°C yield decrease with Tmin increase if yield responds linearly to Rs, which is a good approximation (e.g., Fischer, 1985). The conclusion of Lobell and Ortiz Monasterio (2007) that Rs changes explain the Tmin effects on yield, based solely on the weak negative Rs vs Tmin relationship, is only partly right: 5% yield decrease per °C increase in Tmin comes directly or indirectly (displacement) from the hastening of anthesis.

Commonly increased respiration and hence reduced daily rate of biomass production is invoked as a negative effect of warming. However a recent detailed compilation of crop physiology, edited by Sadras and Calderini (2021), reports few examples of this (rice, soybean, none for wheat) and more broadly supports the notion that respiration is better considered as a fixed proportion of gross photosynthesis. Moreover, in APSIM respiration is included in radiation use efficiency, although radiation use efficiency only declines when Tmean increases above 25 °C. This happened on two days in March in the whole 51 years simulated, and in April, on average 1.8 days a year, usually in the last half of the month. Simulated daily rate of biomass production across years showed

[8] Weather averages refer to Ludhiana, February-March, the critical months of wheat in the Punjab.

[9] This is less than but not significantly different from the slope with the simulated values (140 kg/ha/d, Section 4.3)

no relationship the Tmin or Tmax variation, only to that in Rs.

Notwithstanding the likely absence of an effect of warming effect on respiratory losses, alongside the dominant influence of Tmin variation on PY (and FY) and on days to anthesis, the very weak effect of Tmax J-M variation was surprising. The weak relationship between Tmin and Tmax variation avoids confounding of variation in these variables and may be unique to the Yaqui Valley climate, for only a few other wheat regions show such a weak relationship (Lobell and Ortiz-Monasterio, 2007). As already mentioned, the range and standard deviation of Tmin J-M was 20–30% greater than that of Tmax J-M over the study period, but this is too small a difference to explain the contrasting relationships to phenology and yield. However, a possible explanation of the weak effect of Tmax variation is that Tmax often exceeded the optimal or cardinal temperature for acceleration of development (which is recently estimated for wheat to be 27.5 ^{o}C, Wang et al., 2017, more or less agreeing with the earlier review of Porter and Gawith, 1999). Clearly temperature exceeded this Topt more in years with a high Tmax J-M. For example the warmest year for Tmax J-M (1996 with 28.2 ^{o}C) had 56 days with Tmax equalling or exceeding 27.5 ^{o}C and the coolest year (1973 with 23.5 ^{o}C) only 9 days. For 1969–2019 when daily temperature data was available, adjusting daily Tmax to 27.5 ^{o}C when 27.5 ^{o}C is exceeded in these two extreme cases gives an adjusted Tmax J-M in 1996 of 26.8 ^{o}C, but changes that for 1973 little (23.4 ^{o}C), thus reducing the Tmax J-M range from 4.7 ^{o}C to 3.4 ^{o}C. However, adjusting all Tmax J-M values accordingly does nothing to improve the poor relationship of Tmax J-M variation to that in Yaqui Valley FY for 1980–99 or 2000–19, or that to days to flowering and PY in the Honsdorf 8 year data set. More drastic discounting such as subtracting 1 ^{o}C for every 1 ^{o}C that Tmax J-M exceeds 27.5 ^{o}C reduced its range further, to 2.0 ^{o}C, with no improvement in the FY relationships, nor the PY or days to anthesis ones. Due to a lack of days to anthesis data from irrigated environments like the Yaqui Valley the proposed response of this rate of development to temperature above 28 ^{o}C (notwithstanding Porter and Gawith, 1999; Wang et al., 2017) is quite uncertain. Even so, an improved heat sum algorithm, based on estimated 3-hourly temperatures and a T opt of 27.5 ^{o}C, is proposed for APSIM Wheat (Enli Wang pers. comm.), but was unavailable in the version we used.

A second hypothesis, possibly complementing the Topt one above, to explain the weak influence of Tmax variation on FY (and days to flowering) is that the crop doesn't experience the recorded full extent of higher air Tmax because of greater transpirational cooling of irrigated wheat in higher Tmax days and years. Canopy temperature depression (CTD) relative to air temperature was shown to be 6–9 ^{o}C with modern wheat cultivars at a warmer and drier irrigated site in Mexico (Tlaltizapan, 18^{o} N, 99^{o} W, 940 masl, Amani et al. (1996)). Also in the Yaqui Valley, Fischer et al. (1998) reported three years of Jan to Mar canopy temperature measurement: while Tmax J-M rose steadily from 1993 to 1995 (25.7–27.0 ^{o}C), so did CTD (3.1–5.4 ^{o}C) such that canopy temperature on the measurement dates actually decreased (22.6–21.6 ^{o}C). This supported the hypothesis that variation in canopy temperature is not related to variation in Tmax. However, the sample of days and years was small. Prediction of CTD in irrigated wheat is possible using the general positive relationship between CTD and vapour pressure deficit (VPD) developed in Arizona for irrigated wheat with fully open stomata (e.g., Idso et al., 1981). The recent period 1995–2015 had reliable VPD records permitting calculation of VPDmax (i.e., VPD reached at daily Tmax). However, no relationship was found between VPDmax J-M and Tmax J-M ($R^2 = 0.014$), because vapour pressure J-M was greater in years with higher Tmax J-M ($R^2 = 0.472$ **). Using the relationship from Idso et al. (1981),[10] measured VPDmax values predicted CTD variation unrelated to Tmax J-M ($R^2 = 0.013$) and CTD on average close to 1.7 ^{o}C below air temperature across all years regardless of Tmax J-M variation. This result seems clear, but more data needs to be collected on canopy temperatures throughout the whole 24-h cycle which presumably drives phenology, before canopy cooling in years with higher Tmax can be ruled out as a factor. Besides a final observation is that vapour pressure was higher in years with higher Tmin J-M ($R^2 = 0.387$ *) and therefore VPDmax was related weakly and negatively to Tmin J-M ($R^2 = 0.232^{+}$): the small estimated effect of a 0.16 ^{o}C decrease in CTD per degree increase in Tmin would actually be expected to weakly reinforce the observed hastening effect of higher Tmin J-M on rate of development.

4.4. Relation of results to those from artificial manipulation of crop temperature

Artificial manipulation of crop temperature has the advantage of measuring effects on the crop which are not confounded by variation in other weather variables. Fischer and Maurer (1976) used continuous artificial cooling or heating to show wheat yield was insensitive to small temperature changes in the first month of crop growth in the Yaqui Valley (tillering stage), most sensitive in the second and especially third months, towards the end of which anthesis occurred, while sensitivity varied in the last month (grain filling) depending on source/sink balance. Subsequently a multitude of other treatments in the approximate month before anthesis (shading, CO_2 fertilisation, thinning, photoperiod change) confirmed the positive correlation between PY (and GN) and rate of crop growth (dry matter accumulation) and the negative correlation with rate of development. This period was later named the critical period (Fischer, 1984; Slafer et al., 2001). It coincided with 95% of the dry matter accumulation in the structure of the spikes, running from penultimate leaf emergence to soon after anthesis.

Later artificial heating chamber studies elsewhere of well-watered wheat crops targeted the critical period. For example, Lizana and Calderini (2013) in southern Chile revealed remarkable sensitivity of yield to temperature increase booting to anthesis. A 2.8 ^{o}C increase in Tmean (with both Tmin and Tmax increased by the chambers despite tops being removed by day (but daily Tmax always below 31 ^{o}C, D.Calderini pers comm)), reduced the interval from 12.5 to 10.5 days (about 16%) and grain yield 18%, a yield loss of 9% per day shortening of the period or a yield loss of 6.4%/^{o}C increase, but better described as a loss of 0.61% per day-degree temperature increase.[11]

All the above studies involved increases in both Tmax and Tmin. More appropriately, Garcia et al. (2015) in Argentina used portable chambers in irrigated field plots to increase only night temperature (avg +3.9 ^{o}C), from penultimate leaf emergence until 10 days after anthesis (covering the whole of the critical period). Night heat reduced yield from 6000 kg/ha to 4750 kg/ha (20%); GN and biomass also fell 20%, while harvest index and grain weight changed little. Duration of the critical period was shortened from 39.5 to 33.5 days (15%) and intercepted PAR fell slightly more (18%), as might be expected from the displacement effect. Since radiation use efficiency was unaffected, dry matter produced during the critical period was reduced 16%, and GN and yield were both reduced by 3.3% for every day the critical period was shortened. The yield loss was 5.1%/^{o}C increase in Tmin or 0.31% per day degree temperature increase.[12] At the same location, Gimenez et al. (2021) confirmed similar yield reductions due to elevated night temperatures in the critical period (7%/^{o}C or 3.2% yield loss per day shortening).[13]

These above chamber-derived night temperature sensitivities of

[10] CTD (in ^{o}C) = 0.210 * vpd (in mb) −2.86.

[11] Calculated as 18%/(10.5 × 2.8), assuming the temperature increase applied equally across the shortened period booting to heading, Control yield was 11,000 kg/ha, so yield declined 76 kg/ha/day degree warming.

[12] Calculated as 20%/33.5 x (3.9/2), assuming Tmax was unchanged. Yield declined 18 kg/ha/day degree warming.

[13] Interestingly, Gimenez et al. (2021) found no relationship between yield and Tmin when N deficiency reduced control yield about 40%.

yield (0.61% per day degree increase in the middle of the critical period and 0.31% per day degree for the whole critical period) compare with our Yaqui Valley FY yield response to the increase in Tmin J-M over 90 days of 6.9%/^{o}C, which is 0.15% per day degree increase, assuming no change in Tmax. This supports the notion that yield sensitivity to acceleration of various stages of preanthesis development with warming clearly varies over the 90-day Jan-Mar period analysed (from early tillering until the onset of grain filling). Also, they suggest that the major reason for the Yaqui Valley FY result may lie in the temperature sensitivity of the critical period, as does the fact that February was the individual month with the strongest Tmin influence on FY. Apart from this, however, testing FY against natural temperature variation in shorter specific stages across the crop cycle is not attempted here because of the high degree of natural covariance between Tmin deviations within the Jan - Mar period in any year, a key issue not acknowledged in Nalley et al. (2009). These authors did, however, confirm that over the period 1990–2002 in the ongoing Sayre and Moreno Ramos experiment mentioned in Section 4.2, GN decreased 2.8%/^{o}C natural increase in Tmean in the 30 days up to anthesis.[14] The central role of the critical period in the wheat yield response to temperature suggests possible targets to reduce crop yield sensitivity to chronic warming driving up Tmin (and Tmean). For example, the acceleration of development in the critical period could possibly be slowed by manipulating photoperiod sensitivity (e.g., Slafer et al., 2001; Botright Acuña et al., 2019).

None of the above explains definitively why variation in Tmax does not influence the rate of development (or yield) in our empirical regressions. Future experiments with separate daytime and night-time warming treatments, and continuous 24-hour measurement of shoot apex temperature both in the natural environment and with temperature manipulation, would be informative.

4.5. Conclusions

Our study has highlighted that annual variation in Tmin during key months of the irrigated wheat cycle has a much stronger negative correlation than Tmax (or Tmean) with the rate of wheat development and grain yield, both FY and PY. This has not been reported previously over such a long time period in analyses of wheat response to temperature and is relevant to crop modelling and to climate change. A similar result, at least with respect to FY, was seen in the Punjab of India, albeit over a shorter number of years. These results may be specific to irrigated wheat in warm dry winters and especially the coastal climate of the Yaqui Valley of north-west Mexico but surely needs wider study. Correcting FY trends for the Tmin variability notably improved the estimate of the linear annual technology-driven uptrend in FY in two cases out of three. In contrast to Tmin variation, that in Tmax were almost undetectable in its effect on FY across the 60 years, and on days to anthesis across 8 years of accurate measurement. Neither supraoptimal Tmax values for the response of development rate to temperature, nor greater canopy cooling when higher Tmax values occur appear to explain the weak influence of Tmax. However, 24 h monitoring of canopy temperature is lacking. The Tmin effect found here appears to be closely linked to the rate of development of the irrigated wheat, especially in the critical 30 days up to the end of anthesis important for GN determination, and thereby having a large influence on PY and FY. When combined with results from experiments elsewhere artificially increasing crop night temperature, our FY results are seen to reinforce the importance of Tmin during this critical period in yield determination. It also highlights the need for more attention to ways of increasing the duration of the critical period and hence radiation capture if PY is to be raised in general and chronic warming countered in particular.

[14] This is a partial derivative so it relates only to annual Tmean variability, independent of any variation in Rs. The effect of Tmin alone was not tested.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

The crop and weather data of this study are freely available on Dataverse: https://hdl.handle.net/11529/10548614.

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