Elucidating the impact of temperature variability and extremes on cereal croplands through remote sensing.

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Abstract

Remote sensing derived wheat crop yield-climate models were developed to highlight the impact of temperature variation during thermo-sensitive periods (anthesis and grain-filling; TSP) of wheat crop development. Specific questions addressed are: can the impact of temperature variation occurring during the TSP on wheat crop yield be detected using remote sensing data and what is the impact? Do crop critical temperature thresholds during TSP exist in real world cropping landscapes? These questions are tested in one of the world's major wheat breadbaskets of Punjab and Haryana, north-west India. Warming in the average minimum temperatures during the TSP had a greater negative impact on wheat crop yield than warming maximum temperatures. Warming minimum and maximum temperatures during the TSP explain a greater amount of variation in wheat crop yield than average growing season temperature. In complex real world cereal croplands there was a variable yield response to critical temperature threshold exceedance, specifically a more pronounced negative impact on wheat yield with increased warming events above 35˚C. The negative impact of warming increases with a later start-of-season suggesting earlier sowing can reduce wheat crop exposure harmful temperatures. However, even earlier sown wheat experienced temperature-induced yield losses, which, when viewed in the context of projected warming up to 2100 indicates adaptive responses should focus on increasing wheat tolerance to heat. This study shows it is possible to capture the impacts of temperature variation during the TSP on wheat crop yield in real world cropping landscapes using remote sensing data; this has important implications for monitoring the impact of climate change, variation and heat extremes on wheat croplands.

Introduction

The wheat crop is crucial to support global food security with the largest global cropland coverage (Thenkabail *et al.*, 2012). Yet, similar to other cereal crops its level of production and productivity is vulnerable to a changing climate. Increases in mean growing season temperature, an increase in the frequency of extreme heat stress events at key phenological stages (e.g. the thermo-sensitive anthesis and grain filling periods), uncertain precipitation futures and increased risk of droughts and subsequent moisture shortages all have a potentially negative impact on wheat crop yield (Ortiz *et al.*, 2008; Asseng *et al.*, 2012; Lobell & Gourdji, 2012; Lobell *et al.*, 2012; Gourdji *et al.*, 2013a; Koehler *et al.*, 2013; Teixeira *et al.*, 2013). Across the world's major wheat croplands, the thermo-sensitive periods (TSP) of crop development coincide with the timing of highest average maximum temperatures annually (Asseng *et al.*, 2010), and growing season temperature and extreme heat events during the TSP are projected to increase in the next century (Gourdji *et al.*, 2013a; Mathison *et al.*, 2013; Teixeira *et al.*, 2013). Climate change impacts are already limiting wheat crop yields globally: models indicate that warming trends since 1980 led to a 5.5% reduction in wheat production (Lobell *et al.*, 2011). Model projections of increased exposure to heat stress during the TSP up to 2100 suggest that suitable adaptations need to be implemented urgently to secure climate resilient wheat production (Teixeira *et al.*, 2013; Deryng *et al.*, 2014).

The underlying agricultural system (e.g. access to irrigation, cultivar type, soil type and ecosystem services), which varies within and between cropping landscapes, can increase or decrease the sensitivity of wheat crops to harmful climate impacts (Luers *et al.*, 2003; Luers, 2005; Asseng *et al.*, 2010; Gourdji *et al.*, 2013b; Teixeira *et al.*, 2013). For example, access to sufficient irrigation can enable transpiration which cools canopy temperatures relative to atmospheric temperatures, reducing the potential negative impact of warming during the TSP on the crop (Wassmann *et al.*, 2009; Asseng *et al.*, 2010; Gourdji *et al.*, 2013a; Teixeira *et al.*, 2013). Therefore, to understand the impacts of climatic variation, and specifically heat stress during the TSP, on wheat crop yields as it occurs in real world cropping landscapes requires the ability to observe and test a variety of temperature variables whilst capturing the spatial variation in the underlying agricultural system. Studies exploring the impacts of climatic variables on wheat crop yield are more informative to climate resilient adaptation when they include local or regional detail. This is because potential adaptations often include shifting dates of cropping systems, implementing zero-tillage to avoid periods of heat stress co-occurring with the TSP, and the need to be sensitive to location-specific double/triple cropping rotations (Lobell *et al.*, 2012, 2013; Teixeira *et al.*, 2013).

Crop yield-climate interactions are usually explored using either (i) crop simulation models which aim to replicate crop physiological responses to climatic variation (Challinor *et al.*, 2005; Asseng *et al.*, 2010; Koehler *et al.*, 2013) or (ii) regression models trained with crop yield and climate data aggregated within administrative boundaries (Lobell & Burke, 2010; Schlenker & Lobell, 2010; Rowhani *et al.*, 2011; Urban *et al.*, 2012). Crop simulation models are often complex and require large amounts of input data to represent the underlying complexity of the agricultural system (Welch *et al.*, 2010; White *et al.*, 2011); they are, therefore, limited in their application over large spatial extents. For example, a recent global crop model inter-comparison project simulated climate change impacts on crop yield at a 0.5° spatial resolution (Rosenzweig *et al.*, 2014); this will aggregate farm and field level crop yield variability. This issue is particularly pertinent in low-latitude regions where there is the largest concentration of small and marginal farmers with a heterogeneous landscape and crop yields are projected to be most vulnerable to climate change impacts (Challinor *et al.*, 2014; Rosenzweig *et al.*, 2014). Alongside aggregating spatial variability in agronomic conditions, crop simulation models applied at a global level require simplification of agronomic practices; for example, specifying either full irrigation or no irrigation which will introduce further uncertainty in simulated yields (Rosenzweig *et al.*, 2014).

Moreover, often crop simulation models do not capture the differential impacts of heating events during key phenological stages well. In a review of 221 peer-reviewed climate-crop simulation model studies only 14 partially or fully addressed the issue of heat stress (White *et al.*, 2011). Deryng *et al.*, (2014) use the PEGASUS 1.1 crop simulation model to test the impact of projected changes in heat stress during the TSP on crop production. Whilst this study suggests heat stress during the TSP will limit crop yields it is limited by only using one crop simulation model and the ability to accurately capture the dynamics in the underlying agricultural system such as rates of irrigation application, farmer decisions on planting dates and using fertiliser application data aggregated to national levels (Deryng *et al.*, 2014). A multi-model comparison of different crop model projections of temperature impacts on wheat crop yield suggested that differences in crop model structure, parameterisation and representation of temperature impacts was a larger source of uncertainty than uncertainty in climate projections (Asseng *et al.*, 2013). This issue was echoed in another multi-model study assessing climate change impacts on crop yield where differences in the processes the models simulated and how the models were parameterised led to uncertainty in projected climate impacts (Rosenzweig *et al.*, 2014). In this global gridded crop model inter-comparison study it was also noted that few models simulated heat stress at critical crop development stages such as the TSP. Crop model uncertainty was also deemed a larger or equivalent source of uncertainty than that introduced through climate models when simulating wheat yield under future climates using the Global Large Area Model (GLAM) (Koehler *et al.*, 2013). Studies have shown that CERES and APSIM crop simulation models underestimated the shortening of the wheat growing season when exposed to increased heat stress events (Lobell *et al.*, 2012). This suggests that climate-crop simulation models may underestimate the true negative impacts of climate change on crop yield; this is pertinent given projected future warming and increases in extreme heat days (Gourdji *et al.*, 2013a; Mathison *et al.*, 2013).

In contrast, crop yield-climate models trained at the administrative boundary level aggregate the complexity of the underlying agricultural system which can be problematic in heterogeneous agricultural landscapes. Also, crop yield-climate models trained at the administrative boundary level cannot capture the differential impact of climatic variables at varying phenological stages such as heat stress during the TSP, thus, missing information to inform optimum climate resilient adaptations.

In this paper, we demonstrate how remote sensing data can be used to quantify the impacts of temperature during the TSP on wheat crop yields in real world cropping landscapes, thus, overcoming the limitations of the two, previously discussed approaches. The local detail captured in remote sensing data enables a more appropriate representation of spatially heterogeneous agricultural systems. Remote sensing estimates of crop production incorporate measures of underlying system factors within a pixel (e.g. farmer decisions, access to irrigation, sowing date). The repeat coverage of remote sensing enables monitoring of crop phenology at a fine spatial resolution across a large spatial extent. This, therefore, enables the discrimination of temperature events and warming which occur at different phenological stages, such as the TSP, and an assessment of their impacts on final crop yield.

Here, remote sensing data were used to train crop yield-climate models to assess:

(i) **Can the impact of temperature variables occurring during the TSP on wheat crop yield be detected from remote sensing data?** Previous studies have used remote sensing data to quantify the role of extreme heat events occurring over an entire growing season on the green season length of wheat crops (Lobell *et al.*, 2012). Here, the potential for detecting the impact of temperature variables occurring during the TSP on final crop yield from remote sensing data is tested. This will have important implications for being able to monitor the impact of a warming climate on levels of crop production in croplands across the world given the global coverage of remote sensing.

(ii) **What is the impact of temperature variables occurring during the TSP on final crop yield in real world cropping landscapes?** Remote sensing monitoring of wheat cropping landscapes captures the temporal dynamics of crop development, similar to phenological development within crop simulation models. Yet, remote sensing monitoring captures spatial differences in crop development and incorporates direct measures of the underlying agricultural system (e.g. irrigation, farmer decisions) which are difficult to represent in crop simulation models.

(iii) **If crop critical temperature thresholds during the TSP exist in real world cropping landscapes?** Studies exploring the impact of heat stress during the TSP on crop production often assume a universal crop critical temperature threshold;

though this threshold varies through the literature (Porter & Gawith, 1999; Lobell *et al.*, 2012; Deryng *et al.*, 2014). Often these studies do not test for variability in crop critical temperature thresholds occurring due to agricultural system specific factors such as irrigation enabling transpiration cooling. Studies which have tested a range of temperature thresholds did not focus specifically on temperature during the TSP (Schlenker & Roberts, 2009).

These research questions are tested in the wheat croplands of Punjab and Haryana in north-west India, a major global wheat breadbasket, which was heavily developed using Green Revolution advances and favourable government policy since the 1960s and 1970s (Murgai *et al.*, 2001; Aggarwal *et al.*, 2004; Perveen *et al.*, 2012; Ojha *et al.*, 2013). The wheat crop in the region supports, directly, the livelihoods of tens of millions of people and also supports national government procurement for buffer stocks and national food security and welfare schemes (Aggarwal *et al.*, 2004; DES, 2012; Perveen *et al.*, 2012). Key to the Green Revolution in Punjab and Haryana was the development of an extensive irrigation infrastructure to support wheat cropping during the dry *rabi* season (November – April) (Aggarwal *et al.*, 2004; Ojha *et al.*, 2013). In the 2010-2011 growing season 98.8% and 99.4% of the wheat crop were irrigated, and 80% and 84% of annual precipitation in a normal year falls during the monsoon outside the wheat growing season, in Punjab and Haryana respectively (DES, 2012) (Fig. 1). Therefore, water availability and precipitation variability are unlikely to be limiting factors for wheat crop yield; however, there is a marked rise in temperature through the latter half of the wheat growing season when the TSP occurs (Fig. 1). Also, the supplementary material in Lobell *et al.*, (2012) highlights the increased frequency of extreme heat events (daily maximum temperature > 34 ˚C) during the latter stages of the wheat crop growing season in this region (March and April). This makes this region a suitable site to test for monitoring temperature impacts during the TSP on final wheat crop yield

Materials and methods

MODIS MOD09A1 8-day composites of land surface reflectance covering Punjab and Haryana for the years 2002 to 2007 were assessed for quality (i.e. not cloud contaminated) with ‘bad pixels’ as defined by the MODIS Quality Assurance data removed and gap-filled following (Peng *et al.*, 2011). Pixels corresponding to wheat cropping were extracted per-year using a variety of land cover masks (Xiao *et al.*, 2005, 2006), and a spectral matching technique (SMT) classification procedure (Thenkabail *et al.*, 2007). The SMT provided a statistical match between the shape and amplitude of wheat crop phenology and pixel phenology via a spectral similarity value (SSV) (Thenkabail *et al.*, 2007). R^2 values for the relationship between remote sensing-derived wheat crop extent and district-wise land use statistics (http://lus.dacnet.nic.in/) ranged between 0.86 and 0.92 between 2002-2003 and 2006-2007. Phenology was generated from the MODIS data using the enhanced vegetation index (EVI) which provides a measure of vegetation vigour, photosynthetic activity and biomass (Pettorelli *et al.*, 2005). The gap-filled EVI values were smoothed using a Savitzky-Golay filter which included a fitting bias towards maximum values. This removes noise and fluctuation in temporal EVI profiles due to cloud cover and atmospheric contamination and accounts for the negative bias in reflectance measured at the sensor (Chen *et al.*, 2004). Extracting only wheat pixels minimised error from non-wheat land covers propagating up to the crop yield-climate models (Atzberger, 2013), ensuring that the models captured the interaction between climatic variables and crop yield accurately.

Crop yield was estimated per-wheat pixel for the 2002-2003 to the 2006-2007 growing seasons using a cumulative sum of EVI values over an approximation of the TSP (CUM-EVI$_{(TSP)}$). The period of maximum EVI has been shown to correspond to heading date in cereal crops (Sakamoto *et al.*, 2005). Teixeira *et al.*, (2013) found that a 30 day period around the reproductive crop development phase represented the TSP and captured extreme heat impacts on crop yield. A 30 day period post maximum EVI was taken to represent the TSP. A cumulative sum (or integration of vegetation index (VI) values) and maximum VI values are used commonly as surrogate measures of vegetation productivity and crop yield (Pettorelli *et al.*, 2005; Funk & Budde, 2009; Vrieling *et al.*, 2011; Rembold *et al.*, 2013). VI values post-peak growing season often provide more accurate predictions of crop yield as they correspond to the reproductive and grain filling development stages of cereal crops (Funk & Budde, 2009; Rojas *et al.*, 2011). CUM-EVI$_{(TSP)}$ was significantly (p<0.01) correlated with district-wise wheat crop yield and production between 2002-2003 and 2006-2007 (Fig. 2; http://apy.dacnet.nic.in/). The R^2 values for the regression relationship between CUM-EVI$_{(TSP)}$ and district-wise crop yield are stronger than those obtained using Landsat data to estimate district-wise wheat crop yield in north-west India using the Monteith method (Lobell *et al.*, 2010). The R^2 value for the CUM-EVI$_{(TSP)}$ crop yield model used here was 0.6 (Fig. 2a) whereas the R^2 value in the Lobell *et al.*, (2010) study was 0.28. The correlation for the regression relationship between CUM-EVI$_{(TSP)}$ and district-wise crop yield is also comparable to the correlations obtained with statistical models estimating crop yield from MODIS EVI data in the USA (Bolton & Friedl, 2013). This suggests that in relatively homogenous cropping landscapes (e.g. the USA or Punjab and Haryana) the temporal detail in MODIS data enabling monitoring during the yield sensitive TSP is of greater importance to yield prediction than the spatial detail of Landsat data (MODIS: daily imagery, 8-day composite, 500m spatial resolution; Landsat: 16-day imagery, 30m spatial resolution). However, this trade-off should be evaluated on a crop-by-crop, location-by-location and sensor-by-sensor basis. The larger correlation between CUM-EVI$_{(TSP)}$ and district-wise crop production compared to crop yield is likely due to greater between district variation in cropped area and, thus, production (Fig. 2).

The per-pixel predictions of crop yield were integrated with gridded daily precipitation and maximum and minimum temperature datasets to train crop yield-climate panel regression models. The APHRODITE (V1003R1) dataset provided precipitation data (Xie *et al.*, 2007; Yatagai *et al.*, 2009, 2012). The APHRODITE daily temperature product (V1204R1) provides daily mean temperature only, which inhibits exploring the differential impact of minimum and maximum temperature, and extreme temperatures, on crop yield. Therefore, Global Summary of the Day (GSOD) stations in Punjab and Haryana with a near complete record of daily minimum and maximum temperatures were extracted from: (http://www.ncdc.noaa.gov/). Weather stations were included on the basis of spatial coverage over Punjab and Haryana and completeness in temporal coverage with minimal missing data. Conservatively selecting stations with reliable and comprehensive temperature records was appropriate over Punjab and Haryana as there is minimal orographic variability, especially over cultivated lands, which would cause dramatic shifts in temperatures over short distances. The data from these stations were used to generate gridded fields, at the same spatial resolution as the MODIS data, using an inverse-distance weighting algorithm. GSOD weather stations have been used as inputs in the generation of gridded climate products (Yasutomi *et al.*, 2011) and to assess climate impacts on crops in north India (Lobell *et al.*, 2012).

Linear regression models with fixed-effects terms (equation 1) were fitted to explore whether the impact of temperature and extreme heat events during the TSP on crop yield could be detected using remote sensing data.

$$CUMEVI_{(TSP)it} = \beta x_{it} + c_i + \varepsilon_{it} \tag{1}$$

Where *i* refers to pixel *i* and *t* refers to time of observation *t*=2002….2007. x_{it} is the predictor temperature variable in pixel *i* at observation *t*, c_i is the fixed effects term for pixel *i* and ε_{it} is an error term. CUM-EVI$_{(TSP)}$ was regressed against average minimum, maximum and mean temperature and, extreme degree days (EDD) during the TSP. Average daily minimum and maximum temperature were computed separately as they have been shown to have differing impacts on cereal crop yield (Peng *et al.*, 2004; Welch *et al.*, 2010). EDD was defined as:

$$EDD_{(T)} = \sum_{i-1}^{N} DD \qquad DD \begin{cases} 0 \ \ if\ t_i < T \\ 1 \ \ if\ t_i \geq T \end{cases} \tag{2}$$

Where *T* is the threshold temperature for which EDD is computed individually for each temperature from 32-42˚C at 1˚C increments, t_i is the maximum temperature on day *i* and *N* is the number of days in the TSP (*N*=30). Computing EDD above a threshold maximum temperature, increasing with 1˚C intervals enabled assessment of whether declines in yield due to exceedance of critical temperatures during the TSP can be detected empirically from remote sensing data. On the basis of performing a Hausman test, fixed-effects terms were preferred over random-effects terms. The same sign (i.e. positive or negative slope coefficient) in the relationship between temperature variables and crop yield was obtained when using random-effects terms indicating that the results were not artefacts of including fixed-effects terms. Also, we further validated the regression models using a leave-one-out approach; the fixed-effects regression models were performed leaving out temperature and wheat crop yield data for each year in turn.

Including a fixed-effects term allows the regression intercept to vary spatially. It can be thought of as accounting for time-invariant effects of the underlying agricultural system unique to each location (these effects are not specified, but could include omitted variables such as soil condition, fertiliser application and access to irrigation). Through this remote sensing-based approach key climatic stresses in a particular cropping landscape can be elucidated accounting for the differential sensitivity caused by underlying system factors.

Using remote sensing data means that a unique phenology can be captured per-pixel, per-year enabling estimation of phenological parameters such as start-of-season (SOS), end-of-season (EOS) and approximation of the TSP. Coarser spatial resolution yield data (e.g. administrative boundary yield estimates) would mask variation in the timing of key phenological stages. Using coarser spatial resolution yield data would therefore prohibit assessment of intra-growing season sensitivity to climatic variables such as warming during the TSP. SOS, EOS and TSP can be obtained per-pixel to extract climate information relevant only to the exact growing season of the crop or the TSP. This avoids using monthly or seasonal averages of climate data which correspond to normal growing seasons and may retain climate signals not relevant to crop growth and are not sensitive to spatial and temporal changes in the timing and length of growing seasons. Monitoring phenology using remote sensing means that regression models could be fitted for varying SOS dates. This enables assessment of how varying SOS influenced crop exposure to temperature variation and accounts for the fact that varying day length over a season can influence crop development rates (Lobell *et al.*, 2012). This is important as shifting sowing dates and cropping calendars are a potential adaptation to reduce exposure to extreme heat events (Teixeira *et al.*, 2013). Regression models were fitted for SOS on day-of-year 329, 337, 345, 353 and, 361.

Panel-datasets are multi-dimensional in time and space and, thus, can capture a wider range of temperatures which exhibit greater spatial variation relative to temporal variation at one location (Lobell & Burke, 2010). Panel-regression models have shown improved performance (in terms of strength of association) for capturing temperature-crop yield relationships relative to time-series models (Lobell & Burke, 2010). The temporal extent of the panel-data was restricted to five years to mitigate the impact of shifting agricultural practices or technological advances on crop yield. Several studies have incorporated linear, quadratic or cubic regression spline time terms into crop yield-climate regression models to account for such technological development (Schlenker & Lobell, 2010; Rowhani *et al.*, 2011; Hawkins *et al.*, 2013). However, this requires the assumption that the impact of developmental change on crop yield is universal across the spatial extent of the panel. Given the spatial variability in cropping-systems (Panigrahy *et al.*, 2010), and variation in levels of natural, physical, social and financial capital, which influence uptake of agricultural practices (Erenstein *et al.*, 2007), across the panel, utilising a time term to capture development and assuming its spatial universality was not justified. Crop yield-climate regression models trained using panel-data are less sensitive to the temporal extent over which observations were taken (Lobell & Burke, 2010). For example, Welch et al., (2010) detected the signal of minimum and maximum temperature impacts on rice yield using panel data with observations taken over five years.

Results

(a) Temperature during the TSP and crop yield relationship

Average minimum and average maximum temperature during the TSP have greater explanatory power compared to EDD computed with incrementing temperature thresholds and average growing season temperature (Table 1). Increases in average minimum temperature during the TSP and average growing season temperature have a larger negative impact on wheat yield compared to increases in average maximum temperature during the TSP (Fig. 3). However, increases in all temperature variables have a negative impact on wheat crop yield (Fig. 3 and 4). Generally, an increase in the temperature threshold above which EDD is computed registers a greater negative influence on wheat crop yield (Fig. 4). However, a temperature threshold of 35°C had a noticeably larger R^2 compared to all other temperature thresholds (Table 1), there was also an increase in the size of the slope coefficient at 35°C compared to lower temperature thresholds (Fig. 4). The negative impact of temperature during the TSP, determined by both the value of the slope coefficient and the fit of the model, increased with later SOS dates (Fig. 3 and 4; Table 1). For example, for a SOS on day-of-year 329 a per-unit (i.e. 1°C) increase in average minimum temperature during the TSP would result in -0.0453 Tonnes ha^{-1} decrease in wheat yield whereas the same warming for SOS on day-of-year 361 would result in a yield decrease of -0.0792 Tonnes ha^{-1}. The negative impact of exposure to heating events greater than 35°C during the TSP also increased with later SOS dates (Fig. 4). The same sign (i.e. positive or negative slope coefficient) and patterns in the magnitude of R^2 values were observed in the leave-one-out regression models as occurred in the models using the full panel (Supporting Information). This suggests the results from the full panel fixed-effects regression models are robust in capturing temperature impacts on wheat crop yield and are not artefacts of including anomalous years or data points in the regression models.

Discussion

Average minimum and average maximum TSP temperature explain a greater amount of yield variation compared to mean growing season temperature (Table 1). The TSP approximates the reproductive and the beginning of the grain filling development stages. While several studies focus on the impacts of daily maximum temperature or daytime temperatures above a critical threshold during the TSP or the entire growing season (Asseng *et al.*, 2010; Lobell *et al.*, 2012; Gourdji *et al.*, 2013a; Koehler *et al.*, 2013; Teixeira *et al.*, 2013), it was shown here that minimum temperature during the TSP has an equivalent if not greater negative impact on wheat yields (Fig. 3; Table 1). Lobell & Ortiz-Monasterio, (2007) used the CERES-wheat model and historical wheat yield data in Mexico and California to explore the differential yield impacts of minimum and maximum temperatures. Whilst this study also showed the negative impact of warming minimum temperatures on wheat crop yield it noted that the CERES-wheat model mechanism for simulating grain filling did not replicate the impact of minimum or maximum temperatures observed in historical yields (Lobell & Ortiz-Monasterio, 2007). It is important for further research to contribute to greater understanding of the differential impacts of daily minimum and maximum temperature, and associated physiological processes. This is pertinent given an observed (1970-2005) trend of increasing ‘hot nights’ in north-west India during the pre-monsoon wheat growing season (Kothawale *et al.*, 2010) and an observed (1970-2003) increasing trend in winter minimum temperatures (Kothawale & Rupa Kumar, 2005). These results also suggest that the negative influence of average growing season temperature may be due to it capturing heating events during the TSP and, that adaptive efforts to increase wheat crop resilience to warming, should focus on the TSP.

Regressing EDD above incrementing temperature thresholds showed the expected negative impact of increasing temperature during the TSP on wheat crop yield (Fig. 4). These results suggest that wheat yields in Punjab and Haryana are more sensitive to daily maximum temperatures greater than 35˚C rather than a crop-specific critical temperature, often reported as 34˚C for wheat (Hatfield *et al.*, 2011; Lobell *et al.*, 2012; Gourdji *et al.*, 2013a). The impact of cumulative exceedance of 35˚C during the TSP on wheat yield also varied with SOS date (Fig. 4; Table 1); this is consistent with a range of other observational and crop simulation studies which did not reveal a uniform yield response to heating events greater than 34˚C (Fig. 4 and Fig. 8 in Asseng et al., (2010)). It is worth noting that average minimum and average maximum TSP temperature cause a greater, negative rate of change in wheat yields than exceedance of the 35˚C threshold. This indicates that the effect of a critical temperature threshold is less pronounced in real world cereal cropping systems compared to more controlled, experimental environments or modelling frameworks where the critical temperature signal can be isolated (Jagadish *et al.*, 2007; Asseng *et al.*, 2010; Teixeira *et al.*, 2013). There is likely spatial variation in crop variety, irrigation and vapour pressure deficit during the TSP across Punjab and Haryana, but also in croplands across the globe, which will alter wheat crop response to extreme heat events masking the effects of a critical temperature threshold (Porter & Gawith, 1999; Asseng *et al.*, 2010; Gourdji *et al.*, 2013b).

Spatial variation in the quality of irrigation water has been shown to influence wheat crop yield in Punjab and Haryana (Tyagi *et al.*, 2005). However, the pixel specific fixed-effects terms included in the regression models should capture the variability in yield due to variation in irrigation water quality (and other omitted variables). As mentioned in the introduction, due to the timing of the *rabi* wheat growing season outside of the wet monsoon with near complete irrigation (>98% of the wheat crop is irrigated, (DES, 2012)) the wheat crop should not water limited and precipitation should have little impact on final yield. This is confirmed by univariate regression models using growing season total precipitation and TSP total precipitation as predictor variables (Table 2). The slope coefficients for precipitation variables show a very weak negative correlation with wheat crop yield (Table 2); this is contrary to expected theory and is likely an artefact of relatively small amounts of precipitation during wheat growing season and the wheat crop being irrigated. Also, precipitation variables explain a relatively small amount of the variation in wheat crop yield compared to average minimum and maximum temperature during the TSP (Table 1 and 2).

The negative influence of average minimum and average maximum TSP temperature on final wheat yield increased with later SOS dates (Fig. 3). This trend is consistent with observations by Lobell *et al*., (2012) who observed declines in wheat growing season length associated with later SOS dates in north India; this was attributed to increased exposure to extreme heat days (>34 ˚C) later in the wheat growing season. These results (Fig. 3 and 4, Table 1) suggest that climatic events, namely warming during the TSP, are limiting potential wheat yields in Punjab and Haryana. For wheat crops with a later SOS earlier sowing may be an escape route reducing exposure to damaging heat events and, thus, closing existing yield gaps.

Widespread adoption of zero-tillage represents a suitable adaptive, climate-resilient, management strategy with earlier SOS reducing TSP exposure to extreme heat events with subsequent environmental and socio-economic benefits and, no yield penalty (Erenstein & Laxmi, 2008; Jat *et al.*, 2009). However, even wheat crops with a SOS of day-of-year 329, were negatively impacted by warming during the TSP (Fig. 3 and 4; Tables 1). This indicates that alongside reducing later sown wheat crops' exposure to higher temperatures ('escape' strategies) adaptations need to be explored which increase wheat crop tolerance to warming during the TSP to reduce temperature-induced yield gaps (e.g. develop wheat varieties tolerant to extreme temperatures (Gourdji *et al.*, 2013b)). Implementing such adaptations are important given (i) that current temperatures are limiting wheat yield and (ii) projected future warming trends in the wheat growing season and increased frequency of extreme heat days are likely to further limit wheat yields (Gourdji *et al.*, 2013a; Mathison *et al.*, 2013). Such adaptations could have important future food security implications given coincidental pressures of increased demand for food being placed on these croplands due to population growth (Aggarwal *et al.*, 2004), alongside unfavourable warming (Gourdji *et al.*, 2013a; Mathison *et al.*, 2013).

The panel-datasets, developed using remote sensing data, captured the impacts of climate variation on crop yields, specifically temperature variation during the TSP, as its occurs in real world cropping systems, accounting for spatial variation in system-specific factors (e.g. access to irrigation, farmer decisions). The key findings are highlighted below:

- Previous studies have used remote sensing data to demonstrate the impact of increased warm days above 34 ˚C during the entire growing season on shortening growing season lengths for wheat crops in north-west India (Lobell *et al.*, 2012). Here, we have utilised the phenological detail in remote sensing data to isolate the impact of temperature during the TSP (the reproductive and grain-filling stages when final yield is set) on wheat crops in north-west India. This has demonstrated that is possible to monitor what impacts climate change, specifically changes in the temperature variation and extreme heat events, will have on cereal croplands using remote sensing data.

- Warming average minimum temperatures during the TSP have a greater negative impact on wheat crop yield than warming maximum temperatures during the TSP (e.g. *R2*=0.53(Min(TSP)) and 0.38(Max(TSP)) for wheat crops sown on day-of-year 353). This suggests that studies which focus on the negative warming impacts of extreme heat events and maximum temperatures on anthesis, crop reproductive processes and grain-filling should not neglect the impact of warming minimum temperatures. This is pertinent given observed trends of warming night-time and minimum temperatures in northern India.
- Experimental and simulation studies often report 34˚C as a critical temperature threshold for wheat crop growth. However, remote sensing observations accounting for the complexity of a real world cereal cropping landscape revealed a non-uniform yield response after threshold exceedance and a more pronounced negative impact on wheat yield with increased warming events above 35˚C in the Punjab and Haryana region.
- Warming temperatures during the TSP are currently limiting wheat crop production in Punjab and Haryana. The negative impact of warming temperature during the TSP increases with later SOS dates. This suggests that earlier sowing for late sown wheat may mitigate some temperature induced shortfalls in production. However, given that

earlier sown wheat is still negatively impacted by warming during the TSP it suggests there is a need for heat tolerant varieties to prevent temperature induced yield gaps.

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Table 1. R^2 values for average minimum and average maximum temperature during the TSP, average growing season temperature (T) and $EDD_{(T)}$ accumulated above incrementing temperature thresholds when wheat crop yield was regressed on each of them independently, shown for different SOS dates. Only results significant at p<0.001 are shown.

	SOS (day-of-year)				
Variable	329	337	345	353	361
$T_{(TSP)}$(min)	0.25	0.34	0.39	0.54	0.61
$T_{(TSP)}$(max)	0.24	0.39	0.38	0.38	0.43
T	0.06	0.13	0.14	0.10	0.06
$EDD_{(T)}$: 32	0.08	0.11	0.05	0.06	0.18
$EDD_{(T)}$: 33	0.13	0.19	0.15	0.09	0.24
$EDD_{(T)}$: 34	0.10	0.19	0.14	0.08	0.29
$EDD_{(T)}$: 35	0.14	0.30	0.34	0.37	0.54
$EDD_{(T)}$: 36	0.04	0.15	0.17	0.19	0.23
$EDD_{(T)}$: 37	0.13	0.11	0.04	0.08	0.13

Table 2. Slope coefficients and R^2 values for univariate regression model for wheat yield and growing season total precipitation and TSP total precipitation for different SOS dates. Only results significant at p<0.001 are shown.

	Growing season total precipitation		TSP total precipitation	
	Slope coefficient	R^2	Slope coefficient	R^2
329	-0.0014	0.06	-0.0047	0.21
337	-0.0014	0.05	-0.0043	0.16
345	-0.0026	0.11	-0.0036	0.12
353	0.0034	0.18	-0.0031	0.09
361	-0.0033	0.23	-0.0027	0.09

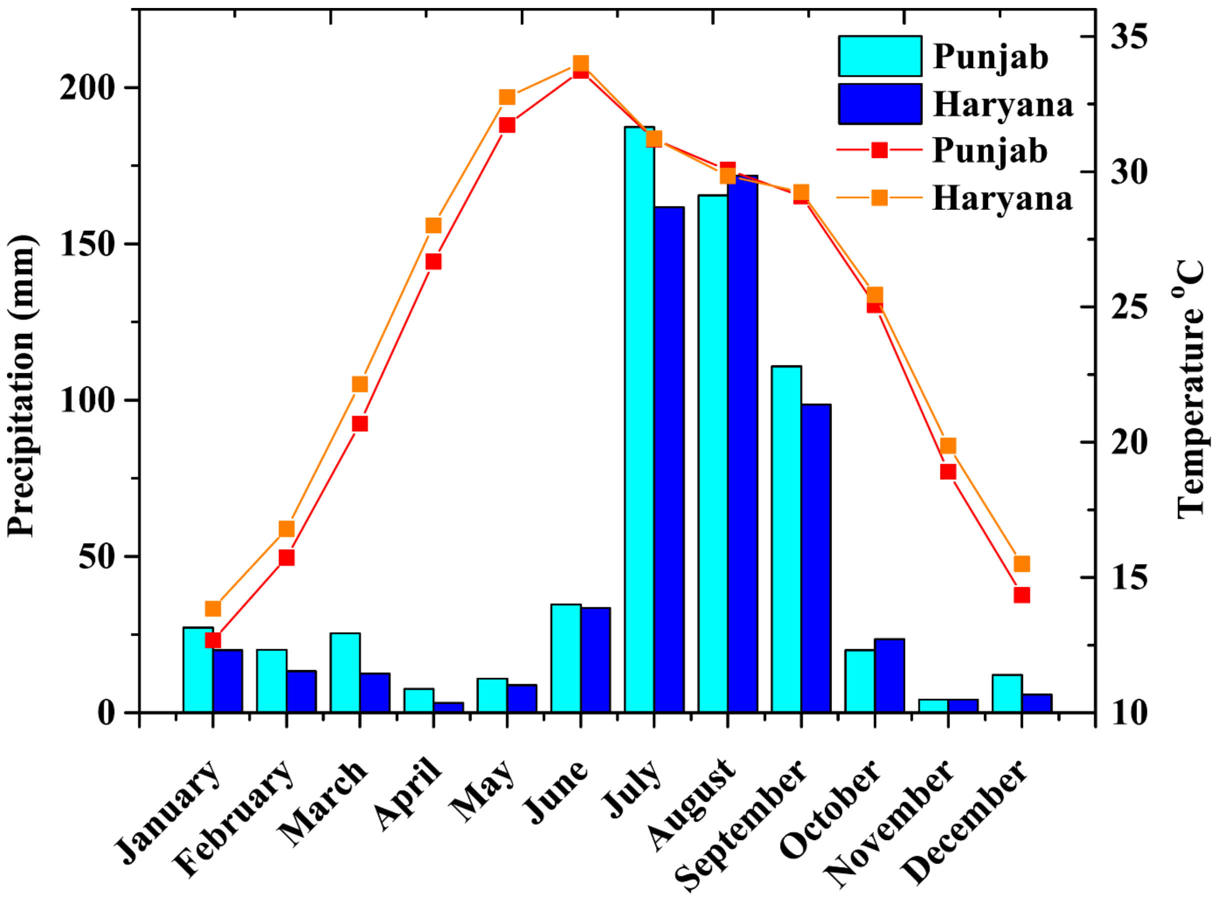

Fig. 1. Normal (1950-2000) monthly precipitation and average daily temperature for Punjab and Haryana (source: www.worldclim.org).

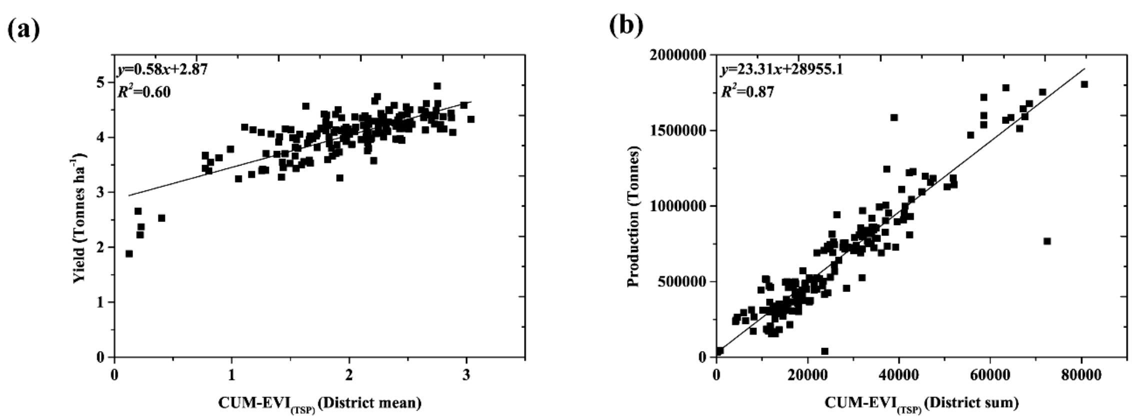

Fig. 2. a) Relationship between remote sensing estimates of district-wise wheat crop yield (CUM-EVI$_{(TSP)}$) and district-wise wheat crop yield as reported by government agricultural statistics (http://apy.dacnet.nic.in/) for the 2002-2003 to 2006-2007 growing

seasons and, b) Relationship between remote sensing estimates of district-wise wheat crop production (CUM-EVI$_{(TSP)}$) and district-wise wheat crop production as reported by government agricultural statistics (http://apy.dacnet.nic.in/) for the 2002-2003 to 2006-2007 growing seasons. The outlier residing near the x-axis between CUM-EVI$_{(TSP)}$ values of 2000-3000 likely reflects erroneous reporting in the Government of India's crop production statistics for the district of Bhiwani in 2005-06. Production of wheat in Bhiwani was 425000, 456000, 415000 and 527000 Tonnes in 2002-03, 2003-04, 2004-05 and 2006-07; Government statistics reporting an 39000 Tonnes for 2005-06 are therefore likely due to an error in reporting, especially as there was not an associated drop in area under wheat cropping (http://apy.dacnet.nic.in/). The outlier was dropped for the yield model (a) to avoid it introducing error into the prediction of yield throughout the study.

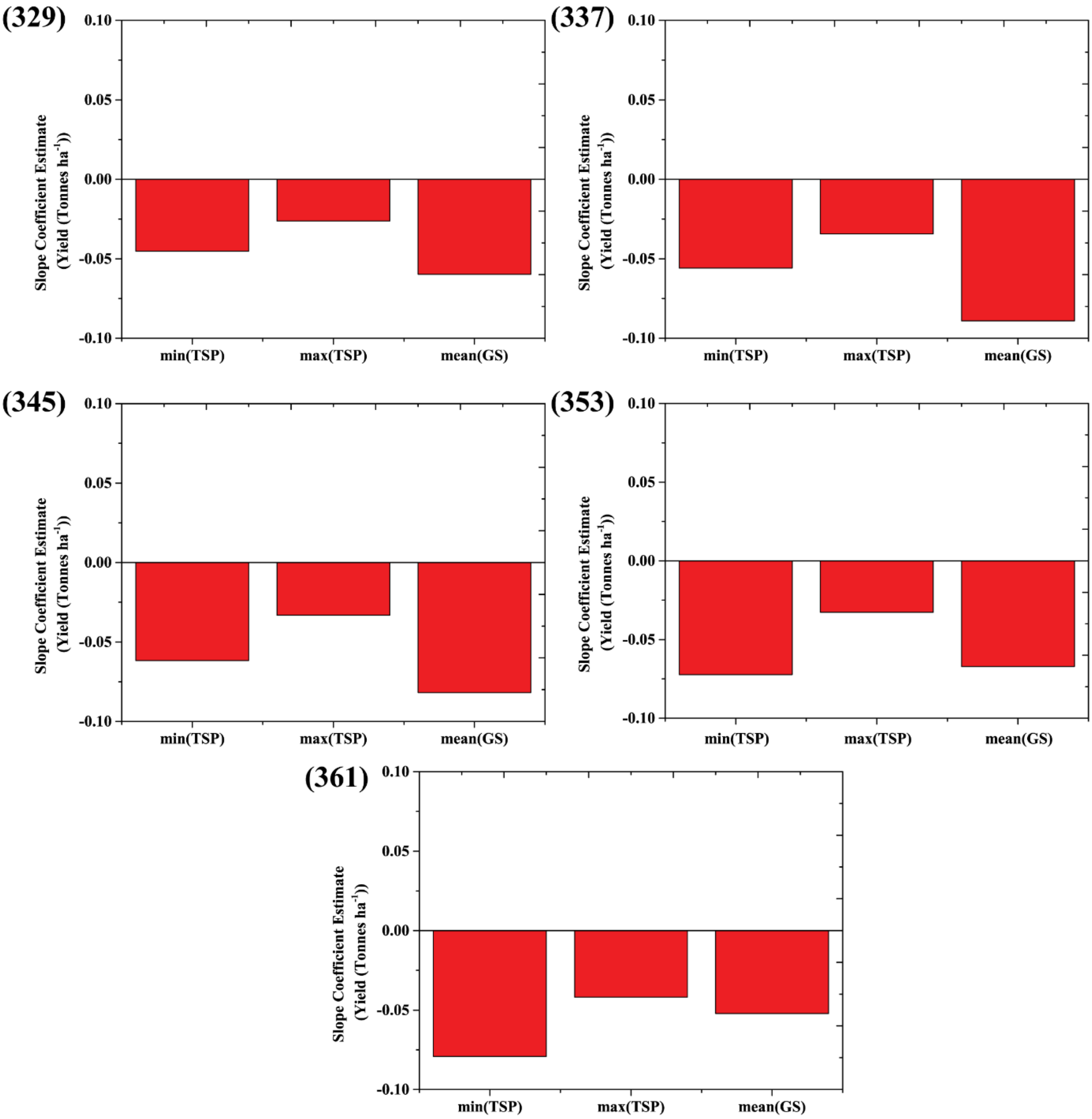

Fig. 3. Slope coefficient estimates in units of Yield (Tonnes ha^{-1}) for per-unit increases in warming (i.e. 1 °C warming) for average minimum temperatures during the TSP min(TSP), average maximum temperature during the TSP max(TSP) and average growing season temperature (mean(GS)). The numbers in the top left hand corner of the plots correspond to SOS date in days-of-year. Only results significant at *p*<0.001 are shown.

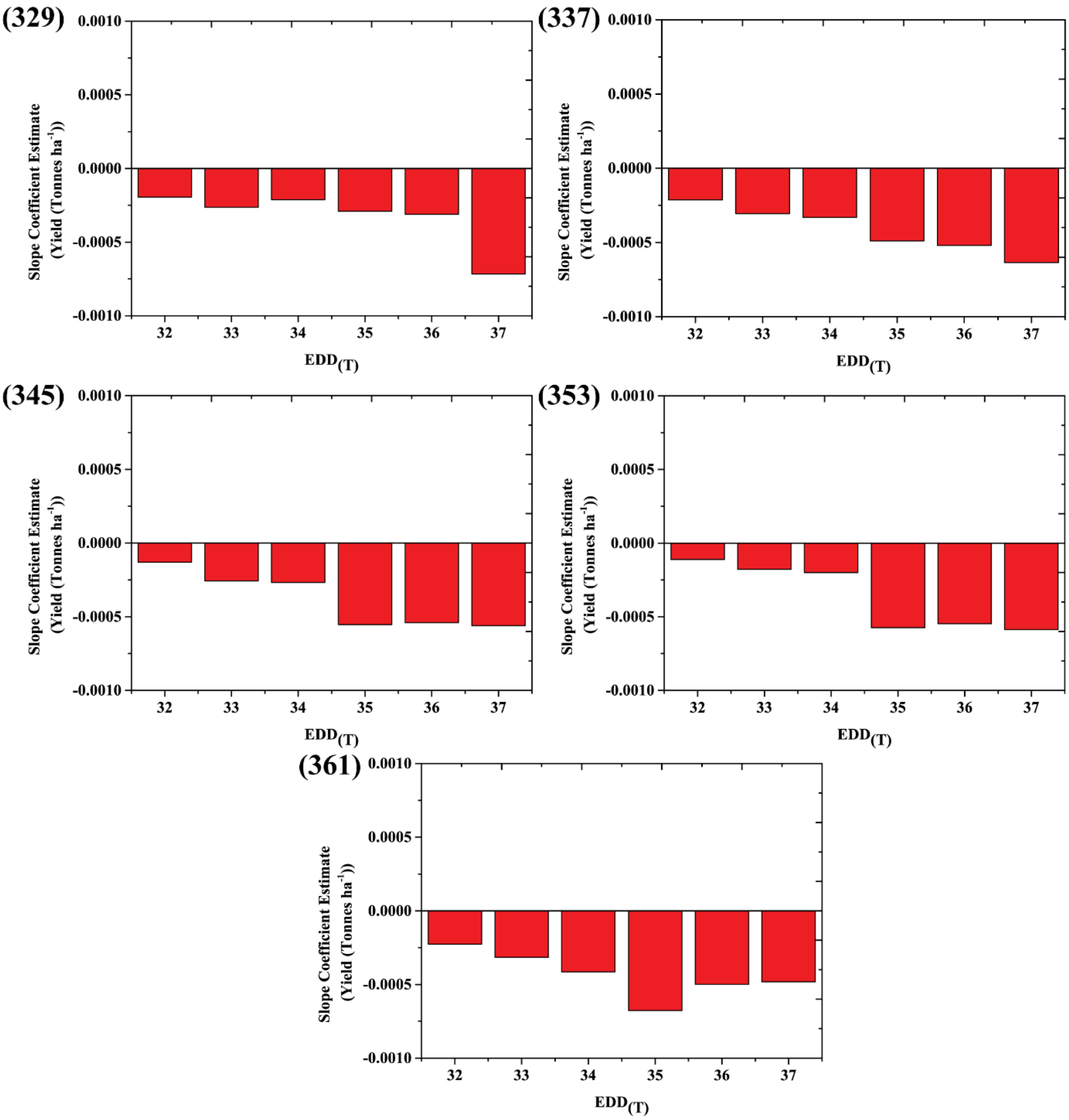

Fig. 4. Slope coefficient estimates in units of Yield (Tonnes ha^{-1}) for per-unit increases in warming (i.e. EDD) for EDD above incrementing temperature thresholds during the TSP. The numbers in the top left hand corner of the plots correspond to SOS date in days-of-year. Only results significant at *p*<0.001 are shown.