Hot spots of wheat yield decline with rising temperatures

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Abstract

Many of the irrigated spring wheat regions in the world are also regions with high poverty. The impacts of temperature increase on wheat yield in regions of high poverty are uncertain. A grain yield–temperature response function combined with a quantification of model uncertainty was constructed using a multimodel ensemble from two key irrigated spring wheat areas (India and Sudan) and applied to all irrigated spring wheat regions in the world. Southern Indian and southern Pakistani wheat-growing regions with large yield reductions from increasing temperatures coincided with high poverty headcounts, indicating these areas as future food security ‘hot spots’. The multimodel simulations produced a linear absolute decline of yields with increasing temperature, with uncertainty varying with reference temperature at a location. As a consequence of the linear absolute yield decline, the relative yield reductions are larger in low-yielding environments (e.g., high reference temperature areas in southern India, southern Pakistan and all Sudan wheat-growing regions) and farmers in these regions will be hit hardest by increasing temperatures. However, as absolute yield declines are about the same in low- and high-yielding regions, the contributed deficit to national production caused by increasing temperatures is higher in high-yielding environments (e.g., northern India) because these environments contribute more to national wheat production. Although Sudan could potentially grow more wheat if irrigation is available, grain yields would be low due to high reference temperatures, with future increases in temperature further limiting production.

Keywords: food security, irrigated spring wheat, poverty, temperature increase, yield impact

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Introduction

Poverty is widespread across the irrigated spring wheat regions in the world (Wood et al., 2010), with wheat being one of the main sources of food in these regions. Current and projected population and economic growth mean that the worldwide demand for food will continue to increase steadily in future (Tilman et al., 2011), and this projected growth in demand includes the irrigated spring wheat regions in the world. At the same time, climate projections show an increase in global temperatures for all the major wheat-growing areas of the world (IPCC, 2014). By 2050, it is projected, for example, that India will warm at a faster rate than the projected global average increase, with projected temperature increases for India ranging from 2 to 4 °C by 2050 and from 3 to 6 °C by the end of this century (IPCC 2014). The warming is also relatively greater in wheat-growing winter and postmonsoon seasons compared to other seasons of the year. In addition, IPCC (2014) predicts that the number of heat events (days over 30 °C) in main wheat-producing countries like India will double in the next 50 years. Battisti & Naylor (2009) used observational data and outputs from 23 global climate models to show a high probability (~90%) that by the end of the 21st century summer temperatures in the tropics and subtropics will exceed the most extreme mean seasonal temperatures recorded from 1900 to 2006.

The increase in temperature will accelerate crop phenological development and result in a shorter growing season for wheat (Wall et al., 2011; Lobell et al., 2012; He et al., 2015). In addition, wheat crops are already exposed to increasing temperature extremes across
major wheat-growing areas (Asseng et al., 2011). This trend is projected to continue in future across agricultural regions (Gourdji et al., 2013; Koehler et al., 2013) and will potentially reduce grain yields at global ‘hot spots’, as shown by the Global Agro-Ecological Zones Model for rainfed crops (Teixeira et al., 2013). Yield reductions of 2–8% for every 1 °C increase above an optimum temperature for wheat of 15 °C have been measured for a range of cultivars under controlled (Wardlaw et al., 1989) and field experiments (Wardlaw & Wrigley, 1994). A 6% reduction in global wheat production has been suggested per °C increase in global temperature using a large multimodel ensemble (Asseng et al., 2015).

Wheat is one of the most cultivated crops in the world, and irrigated spring wheat contributes a large proportion to global wheat production (Braun et al., 2010). Wheat ranks first in total harvested area and third in production after maize and rice (FAO, 2015). Wheat is, for example, the most important winter season (October to April) crop in India and is mainly grown with irrigation (90%). India is the second largest wheat producer in the world, after China. Overall production of wheat in India has increased substantially in the past forty years from 12.3 Mt in 1965 to 86.8 Mt in 2011 (FAO, 2015), representing about 12% of global wheat production. The current wheat area is 27.8 Mha in India (FAO, 2015). In contrast, the continent of Africa is the largest wheat-importing region in the world (FAO, 2015). Sudan, the third largest country in Africa, currently uses only one-tenth of its potential arable land for cropping. Sudan produced 0.5 Mt wheat mostly with irrigation on 312 000 ha of agricultural land in 2009–2011 (Negassa et al., 2013) and imported 0.6 Mt of wheat in 2000 (FAO, 2015). The average wheat yield for Sudan is 1.7 t ha⁻¹ (Negassa et al., 2013). The highest experimental wheat yields reported for Sudan are also relatively low and ranged from 1.9 to 3.6 t ha⁻¹, depending on region. However, Negassa et al. (2013) and the FAO have identified potential new regions for wheat production in Sudan, assuming irrigation is available (http://www.fao.org/ag/AGP/AGPC/doc/field/Wheat/africa/sudan/sudanagec.htm). If additional wheat production takes hold in Sudan, it could potentially make Sudan more wheat-self-sufficient and even give the country the ability to supply wheat to neighboring countries, especially considering that the largest importer in Africa is the neighbor Egypt (FAO, 2015).

Crop simulation models (CSM) and statistical models are useful tools to assess the potential impact of climate change on crop production (Lobell et al., 2011; Rosenzweig et al., 2013; Challinor et al., 2014). As crop and statistical models vary in their response to climate factors such as increasing temperature, a multimodel approach has been suggested in the Agricultural Model Intercomparison and Improvement Project (AgMIP; www.agmip.org) to better understand and quantify impact model uncertainty (Rosenzweig et al., 2013). An analysis of the responses of multimodel ensembles to increasing temperatures showed that the model biases of single models were large across major crops (Asseng et al., 2013; Bassu et al., 2014; Li et al., 2015). Multimodel ensemble mean or median simulations were consistently superior compared to any single-model simulation when closely reproducing observations across growing environments of any system variable for wheat crops (Martre et al., 2015), grain yields across crops (Asseng et al., 2013; Bassu et al., 2014; Li et al., 2015), and particularly the response of wheat yields to increasing temperatures (Asseng et al., 2015). In addition, Asseng et al. (2013) showed that at least three to four models are needed for simulations of 2 °C temperature increases to reduce the simulated yield bias to the size of common field experimental errors.

A multimodel ensemble was used to estimate the impact and uncertainty of increasing temperatures on wheat yields in two key irrigated spring wheat regions, India and Sudan, including potential new areas in Sudan. The simulated yield–temperature relationship was then used to estimate yield impacts from increasing temperatures by 2030–2041 across the entire irrigated spring wheat-growing regions in the world and overlaid with poverty headcounts to identify potential future food security ‘hot spots’.

Materials and methods

Four crop simulation models and one statistical model were used for this study and included NWheat v1.55 (Asseng, 2004), DSSAT CERES-Wheat v4.5 (Jones et al., 2003), and SALUS v1.0 simple (SALUS_S) and complex (SALUS_C) (Basso et al., 2010). Details of the statistical model are described by Gourdji et al. (2013). These models were applied at 20 locations in the wheat-growing regions of India and 10 locations in Sudan, including the potential wheat-growing regions identified by the FAO (FAO, 2015). The wheat crops were simulated with no water limitation (assuming full irrigation) and no nitrogen limitations (i.e., potential crop growth and yield). The sowing date of November 14 for each simulated year (DOY 319) was the same for both India and Sudan, representing farmer’s praxis in these regions. As there were no water and N limitations assumed in the simulations, the same loamy soil was used for all locations. A spring wheat cultivar with no vernalization and little photoperiod sensitivity (similar to cv Yecora) was used in the simulations. Spring wheat is often grown over winter in regions with mild winter temperatures like India and Sudan, with no winter dormancy.
periods, compared to cooler regions where winter wheat (with vernalization requirements and winter dormancy) is grown. Two sources of weather data were used: the simulation models used NASA/POWER for all weather inputs, the statistical model used NASA/POWER for humidity and solar radiation, but nearby weather station data for temperature. The NASA/POWER weather data were downloaded from the NASA/POWER website for a 1° × 1° geographic coordinate grid (Stackhouse et al., 2011). For the simulation models, daily weather data from 1984 to 2011 (27 growing seasons) for solar radiation (MJ m⁻²), and maximum and minimum temperature (°C) were used as the baseline temperature (or reference temperature). For the statistical model and a global application, daily minimum and maximum temperature data were interpolated from nearby station data using the methods described in Gourdji et al. (2013), whereas radiation and relative humidity were from the NASA POWER database (Stackhouse et al., 2011). As the same humidity data were used for building the statistical model and making projections, any biases should apply to both periods and not greatly affect the results. Note that rainfall data were not required as no water limitations were assumed.

Observed grain yields from irrigated, high fertilizer input systems were available for multiple years for or near seven sites in India and one site in Sudan from the International Wheat Information System of CIMMYT’s international nurseries. Measured genotypes per location and year were averaged as genotypes differed across locations. As detailed information on crop management was not available for these observed yields, they were used in a qualitative comparison by plotting them together with the 30-location seasonal mean simulated/statistical grain yields over seasonal mean temperatures. Therefore, some of the visual discrepancies between observed and simulated yields at a given seasonal mean temperature could be due to different crop management (e.g., sowing date), the gridded weather data not representing the actual conditions at a specific nursery, occasionally insufficient irrigation, pests and diseases, cultivar effects, or model shortcomings. However, investigating the source of such discrepancies was not subject of this study.

For the increased temperature scenarios, the measured daily maximum and minimum temperatures were increased by 1, 2, 3, and 4 °C. In total, each crop and statistical model simulated 3360 experiments. Simulated differences in yields and yield responses among years at each location (natural temporal variability) and among sites (natural spatial variability) were due to temperature and solar radiation differences (and relative humidity for the statistical model) as soil type, initial conditions, cultivar, and management among the locations were kept constant. The relative grain yield change due to temperature increase was calculated as follows:

Relative grain yield change (%) = \( \frac{(x_f - x_b)}{x_b} \times 100 \).  \( \text{(1)} \)

In this equation, \( x_f \) is the grain yield simulated with increased temperature, and \( x_b \) is the simulated reference (baseline) yield. Average daily temperature was calculated as follows:

\[ \text{Average temperature} = \frac{(T_{\text{max}} + T_{\text{min}})}{2}. \]  \( \text{(2)} \)

Here, \( T_{\text{max}} \) is the daily air maximum temperature (°C), and \( T_{\text{min}} \) is the daily minimum temperature (°C). The growing season temperature (GST) was calculated using the average temperature Eqn (2) between November 14 (sowing date) and the simulated maturity day, which varied among models, locations, and years.

Simulated differences in yields and yield responses among models were due to differences in model structure, equations, and equation parameters, as input variables (e.g., daily weather data) were the same for each model. The simulated spread in yields and yield responses among the models was used to estimate model uncertainty. The multimodel ensemble median was used as the main predictor, and it was shown to be superior to any individual model across environments for wheat (Asseng et al., 2013; Martre et al., 2015), maize (Bassu et al., 2014), and rice (Li et al., 2015) simulations. The multimodel ensemble median was also recently shown to be better than any single model in simulating yield impacts from temperature treatments in field experiments (Asseng et al., 2015). Crop responses are presented as ensemble medians and percentiles. For yield responses, a ±25% spread of the simulated model ensemble median was calculated and used here as an indication of model uncertainty. The 50% range represents a 50% estimated likelihood of a yield response within this range, similar to presented uncertainty ranges in other studies (Asseng et al., 2013).

Global application, climate change, and poverty counts

The relationship between yield impact from the multimodel ensemble median in India and Sudan for one degree temperature increase in seasonal temperature was applied to projected temperature changes across 0.5° grid cells for main irrigated spring wheat regions of the world. Main irrigated spring wheat areas were defined as cells with >10% of all crop area as wheat, >5000 ha irrigated wheat, and at least twice the wheat grown being irrigated. Both irrigated and rainfed wheat areas were from the MIRCA dataset (Portmann et al., 2010), while total crop area was taken from the M3 dataset (Ramanjutty et al., 2008). Temperature data of 0.5° cells were interpolated from nearby station data using the methods described in Gourdji et al. (2013), whereas radiation and relative humidity were downloaded from the NASA POWER database (Stackhouse et al., 2011).

To estimate a near-future temperature change, projected median temperature change from 30 Global Climate Models downloaded from CMIP5 for RCP8.5 for the period 2030–2041 related to the mean temperature from 2000 to 2011 (baseline for future temperature study) was used. The local change of temperature by 2030–2041 was applied to the seasonal mean temperature at a grid cell and translated to a yield impact using the multimodel ensemble median yield impacts from the India and Sudan simulations. As a crude measure of the overall population potentially exposed to food security impacts from wheat yield losses, a map of

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poverty headcounts was used to determine total poverty headcounts for areas at different levels of impacts (Wood et al., 2010). A total of 285 million people currently earn < $1.25 per day and live in areas classified as main irrigated spring wheat regions (as defined above). This corresponds to roughly one-fifth of the total global poverty headcount, meaning that one in five poor people live in areas where irrigated spring wheat provides a substantial share of food and revenue.

**Future food security ‘hot spots’**

Future food security ‘hot spots’ were defined as areas (grid cells) of yield change due to increased temperature impacts being above the top 10%-tile worst impacts by 2030–2041 and having a current above average (across irrigated spring wheat regions) poverty count (for people earning < $1.25 per day). Note, ten grid cells from Northern, Central and South America and eight grid cells from Southern Africa, representing irrigated wheat in these regions, but with none of them coinciding with high poverty counts, are not visible in the chosen window of the global map.

**Results**

Multimodel simulations and statistical regressions were carried out for locations across the main wheat-growing regions in India and Sudan, including potential wheat-growing regions for Sudan (Fig. 1). Mean growing season reference (baseline) temperature increased from north to south and were in general higher in Sudan than in India.

The mean growing season temperature dynamics also differed for both countries (Fig. 2). While the mean temperature was generally high during the season in Sudan, early and mid-season temperatures in India were cooler than in Sudan, but increased to similar mean temperatures for both countries during the later part of the seasons.

Observed and simulated yields declined with increasing seasonal mean temperatures of above 15 °C (Fig. 3). Observed yields varied due to the averaging across several cultivars at each location (indicated by error bars). Observed mean yields also varied for similar mean season temperatures due to different

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Fig. 1 Mean season temperature (based on NASA/POWER data for simulated average growing seasons from sowing to maturity) for study locations where simulations and statistical estimates were carried out in wheat-growing regions (green shaded) for India (left) (http://www.pecad.fas.usda.gov/highlights/2006/02/india_21feb2006/wheat_map.htm) and Sudan (right) (http://www.fao.org/ag/AGP/AGPC/doc/field/Wheat/africa/sudan/sudanagec.htm). Locations in potential wheat-growing regions (locations outside green area) identified by FAO (FAO, 2015) were also included for Sudan.

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temperature dynamics between years. Similarly, simulated yields varied for each model (vertical error bars) and due to different temperature dynamics and differences of in-season temperatures (among seasons of 1984–2010, indicated by horizontal error bars). The simulated yields tended to be consistently above or below the observed grain yields depending on model. The yields calculated with the statistical model tended to be less responsive to the mean temperature change, but were often closer to the observed mean yields than the simulated yields. As a consequence of the various model behaviors, the multimodel median yields came closest to the observed grain yields (Fig. 3).

Across the locations, the simulated number of days to maturity declined linearly by approximately 7 days per degree increase from above 15 °C mean seasonal temperature (Fig. 4). The model uncertainty of maturity date estimates (± 25%-tile of ensemble median) quadrupled from mean season temperature of approximately 15–27 °C. When increasing the temperature by 2 °C at each location, the change in days to maturity followed a similar decline; there was also an increase in model uncertainty, except for the increase in temperature from 13 to 15 °C when the days to maturity declined with the increased temperature, but increased with temperature increase from 15 to 17 °C (Fig. 4). The impact of a temperature increase through increasing the temperature in the weather data can be different to moving from one location to another location with higher temperature, due to different temperature patterns and their impact on phenology. Such difference is less apparent above 17 °C mean seasonal temperature where a warmer location acted like a cooler location with increased temperature.

In irrigated, full nutrient-supplied wheat crops, the main impact from a shorter growing season is a reduced biomass accumulation (not shown) due to less radiation interception. The reduced biomass
accumulation in irrigated cropping systems translated into lower grain yields (Fig. 5). Simulated grain yields declined linearly with increasing seasonal temperatures across locations and similarly with increasing the temperature at each location (Fig. 5a). Interestingly, the uncertainty in yield changes due to increasing temperatures was smaller at higher temperatures compared to cooler temperatures. While the decline in absolute grain yields was linear with increasing temperatures, the relative yield decline (shown for impact per 1 °C temperature change) was exponential (Fig. 5b). The median of the yield decline per 1 °C temperature change is relatively larger at warmer locations with lower mean yields compared to cooler locations. The uncertainty in estimating relative yield change did increase with increasing temperatures, in contrast to the change in absolute yields.

The relationship between the simulated multimodel median relative yield impact and mean season temperature (Fig. 5b) was used to estimate the impact of future climate change by 2030–2041 (compared to baseline 2000–2011) (temperature change only) across all irrigated spring wheat regions of the world with mean seasonal temperatures >13 °C (Fig. 6), assuming similar temperature responses despite possible cultivar differences. Largest negative yield impacts due to increasing temperatures were estimated for southern India, southern Pakistan, Sudan, some parts of Saudi Arabia, and north-central China. When the 10% most impacted regions (>7.7% yield loss) were overlaid with high poverty headcounts, that is more than average poverty headcounts across the entire irrigated spring wheat regions, southern wheat-growing regions of India and Pakistan were identified as future food security ‘hot spots’.

Discussion

The qualitative comparison of simulated and observed data showed large differences across a wide temperature range. Several of the models used in the study were part of a multimodel ensemble in a comparison in which detailed field information was available and simulations of these models came close to observed grain yields (Asseng et al., 2015). Hence, due to missing detailed information from the experiments and adequate irrigation not always being achieved in the field, setting up the simulation models with estimated inputs is likely to explain most of the discrepancies. In addition, evaporative cooling can buffer plant temperature to some extent (Amani et al., 1996; Webber et al., 2016), which is not considered in any of the models used here. Similar to other multimodel ensemble studies, the ensemble median came closest to the observed data compared to any individual model. Therefore, using the multimodel ensemble median is a more precise predictor in simulation studies as shown for wheat (Asseng et al., 2013, 2015; Martre et al., 2015), maize (Bassu et al., 2014), and rice (Li et al., 2015). Five different models were used in this study, which is a sufficient number for the targeted temperature change (Asseng et al., 2013) to reduce the model uncertainty of the ensemble median (e.g., CV of the median of models) to below an average field experimental error (Taylor et al., 1999). A probability range around the ensemble median allowed the quantification of a range of uncertainty of prediction, which in this study was set to ±25% (or 50% most likely probability range) of the simulated ensemble median grain yield. This range indicates a 50% likelihood of a simulated yield response being within this range. A higher simulated
likelihood means a wider range. Other uncertainty ranges around a multimodel ensemble median have been chosen from ±25% to ±40% (Asseng et al., 2013). The uncertainty in simulating absolute yields at locations with higher temperatures declined (more narrow range of prediction), underlying the increasing certainty of simulated impacts with increasing temperatures in this study, is in contrast to Asseng et al. (2015). However, the uncertainty in relative yield impacts with increased temperatures increased similar to Asseng et al. (2015).

High temperatures already limit wheat production in many warmer regions of the world (Rosenzweig et al., 2014), including southern India and Sudan. Further increases in temperatures with global warming will reduce wheat yields in India and Sudan by approximately 0.34 t per ha per 1 °C (above 13 °C), regardless of reference temperature, which is less than reported for a field warming experiment with 0.42 t ha⁻¹ yield decline per 1 °C (above 16.3 °C) (Ottman et al., 2012). Wheat grown in environments below approximately 15 °C can increase yields with increasing temperatures (Fang et al., 2015). However, above a temperature threshold (approximately 13–15 °C for India and Sudan, and 20 °C for the Ottman et al. experiment), absolute grain yields tend to decline linearly with increasing temperature. This means that the relative yield decline above a threshold increases with increasing temperature. Ottman et al. (2012) reported across the temperature range in their experiment (including some frost damaged yields) an average yield decline of 6.9% per 1 °C (the relative decline is larger when excluding frost-affected yields in their experiment). Wardlaw et al. (1989) reported 3–4% yield decline per 1 °C from a survey across several countries. Lobell et al. (2011) have shown that the temperature increase during 1980–2008 has caused a global wheat yield loss of 5.5% per 1 °C temperature increase and indicated that this varies across the globe with a tendency of larger yield losses in the tropics and subtropics, such as India and Sudan. A global simulation study by Asseng et al. (2015) suggested a global wheat yield decline of 6% per 1 °C global temperature increase, also varying across the globe with larger losses in warmer regions. In addition, the present study showed that the relative yield decline does increase with reference temperatures. The wheat yield decline is approximately 5.9% (±0.7%) per 1 °C temperature increase at 13 °C and almost triples to approximately 15% (±2.2%) per 1 °C temperature increase at 27 °C. As a consequence, the relative yield reductions are larger in low-yielding environments due to higher reference temperature in warmer regions like the southern Indian wheat region and in most of Sudan. Therefore, farmers in these warmer irrigated wheat regions are hit hardest by increasing temperatures, in addition to high-impact areas as identified for rainfed wheat cropping systems by Teixeira et al. (2013). As absolute yield declines are about the same in low- and high-yielding regions, farmers with low yields in warmer regions will suffer more from global warming than farmers in cooler, high-yielding regions. This is in contrast to simulation results for sorghum, where in low-yielding cropping systems, because of low fertilizer inputs, simulated yields were less affected by increasing temperatures than high-yielding cropping systems, due to increases in mineralization and N availability (at least for a limited period) with higher temperatures (Turner & Rao, 2013).

If considering the food security of an entire country, the contributed deficit from increasing temperatures to
the national production (e.g., India) is larger from high-yielding environments (e.g., northern India) because these environments contribute more than the low-yielding environments (e.g., southern India) to national wheat production, both because of their higher yields and generally higher planted areas. Hence, while individual farmers in southern India will be hardest hit by increasing temperature, the losses from the cooler northern grain producing regions will be more critical for national food supply.

As the third largest country in Africa and the number ten in wheat imports in the continent, Sudan has the potential to grow more wheat, assuming irrigation is available. Although current grain yields will be low due to high reference temperatures in most regions of this country, some yield increases might be possible with improved crop cultivars and crop management. Improved crop cultivars could include delayed maturity-type cultivars combined with improved heat tolerance suggested by Asseng et al. (2015) as a climate change adaptation option to compensate for a reduced growing period from increased temperatures. Improved crop management could include, for example, extra irrigation and mulching of wheat crops in hot environments with low relative humidity (i.e., high leaf-air vapor pressure deficit). In Sudan, this has been shown to increase wheat yields (Badaruddin et al., 1999), probably due to increased canopy cooling from high transpiration rates (Amani et al., 1996). Contrary to the suggested crop improvements, recent slowing or stagnating yields in many cropping areas of the world (Lin & Huybers, 2012; Ray et al., 2013) indicate that such measures are not enough to offset temperature-driven yield losses. But, reduced fallowing (Betts et al., 2013) and further cropland intensification could cool regional temperatures (Mueller et al., 2016) and increase rainfall around irrigated regions (Alter et al., 2015) to improve crop growing conditions. Nevertheless, increases in temperature will disproportionally limit the current and potential future production of wheat in Sudan compared to cooler wheat-growing regions elsewhere. Hence, to significantly increase wheat production in Sudan, new large areas of land will be needed for wheat cropping. This might be limited due to land suitability (Meissner & Wycisk, 1993; Elmobarak & Mahgoub, 2014) and particularly due to lack of access to sustainable irrigation water in Sudan (MacDonald et al., 2012; Al Zayed et al., 2015; Satti et al., 2015).

When considering changes in temperature by 2030–2041 (compared to a baseline 2000–2011) across all irrigated spring wheat regions of the world with mean seasonal temperatures >13 °C combined with poverty indicators (earnings of <$1.25 per day), the southern wheat-growing regions of India and Pakistan were identified as future food security ‘hot spots’, defined as areas above the top 10-percentile with the worst yield impacts combined with above-average poverty head-counts.

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Conflict of interest

The authors have no conflict of interest to declare.

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