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LETTER

Irrigation-limited yield gaps: trends and variability in the United States post-1950

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Abstract

Irrigated agriculture is generally considered to be more productive than rainfed agriculture at any given location. This difference in crop yield between irrigated and rainfed production ('Irrigation-limited yield gap' or ILYG) is subject to spatio-temporal variability, due to differences in management, environmental conditions, soils, and policy. However, quantification of ILYG and its associated variability remains uninvestigated. In this study, we analyzed the spatio-temporal dynamics of county level-ILYG for nine major irrigated crops in the United States: maize, soybean, spring wheat, winter wheat, alfalfa, sorghum, cotton, barley and oats from around 1950 to 2015. ILYG was found to be highly specific to crop and location and has been increasing, in general, over time, albeit with regional differences. Maize had the greatest ILYG magnitude on a national basis, with cotton ILYG showing highest temporal rates of increase. Increased ILYG variability over the study period was found for all crops, except cotton, which also showed the highest magnitude of long-term mean variability. Maps and key information in this article are significant to irrigation research, policy and decision-making, plant breeding, groundwater withdrawal allocation strategies and producers to identify pertinent regions using historical ILYG for optimizing farm irrigation management strategies to enhance overall national agricultural productivity.

Introduction

Irrigation is practiced on 24% of global cropped area, which grows approximately 40% of global agricultural commodities and hence, is an integral part of the global agricultural industry [1]. Irrigation development has been playing a substantial role to help achieve higher yields generally, as well as making agricultural production systems more resilient, robust and stable against climate variability and change [2, 3]. Irrigation availability enhances crop performance in dry spells and in regions with insufficient and/or non-uniform precipitation distribution. It has been reported that in order to sustain future food production against climate change effects, irrigation expansion must remain a primary investment [4, 5]. Irrigation has been able to decouple US crop yields from climate and hence can act as a climate-modulating tool in the future [3]. In absence of irrigation, the planet would incur losses equivalent to a fifth of existing cereal production [1]. Owing to these ideal production metrics and security of irrigated crop production and well as climate-resiliency, US irrigated regions (supplementary figure S1 is available online at stacks.iop.org/ERC/1/061005/mmedia) are pivotal for maintaining the national food security.

Evaluation of irrigated and rainfed agricultural production regions entails quantifying historical variability in crop yields. Past work has focused on trends and variability associated with a range of crop yields globally [6–13] and regionally [14–21]. Although the objectives of these studies vary to some extent, (primarily, estimating yield patterns, stagnation and climate-fingerprint on crop yield variability etc), they all rely on various statistical measures associated with crop yield data. These statistical analyses are carried out primarily by using a
pooled (weighted average) of irrigated and rainfed yields for a geographical unit, which is reported by agricultural statistics agencies. This technique, while advantageous for studying crop yields over large spatial domains in general, masks the considerable variability that exists among irrigated and rainfed yields. Nevertheless, this issue has been taken care of, although partially, in other studies that discussed variability in irrigated and rainfed crop yield characteristics separately [12, 16, 21]. Among these advances in the crop yield characterization, one aspect of crop yield variability research remains unexplored, which is, characterization of site-specific differences between irrigated and rainfed yields. This exercise can potentially provide useful comprehension of performance and evaluation of irrigation practices at a given site.

In this study, we refer to the difference between irrigated and rainfed yield (i.e. yield increase due to irrigation) as ‘Irrigation-Limited Yield Gap’ (or ‘ILYG’) and use this term from hereon. The ILYG essentially indicates the incremental yield improvement that results if a representative rainfed production site is converted to irrigated production, and conversely, yield loss if irrigation water is diverted to other consumers besides irrigation or as a result of declining aquifer levels. An important consideration in the definition of ILYG is that the two contrasting production sites in question should have similar agrometeorological and other production conditions. Irrigated crop yields have greater rates of increase over time than their rainfed counterparts [21]. Hence, the ILYG at any location implicitly represents the change dynamics of both its parent variables (irrigated and rainfed yields). It should be noted that we do not assume the irrigated production scenario to be an ideal setting as other challenges can exist in practice which prevent it from producing potential yields [22, 23]. Instead, we intend to compare historical rainfed production systems with their irrigated peers to quantify the readily attainable yields via irrigation adoption without any additional efforts in technology and management.

Our specific objectives are to (a) quantify ILYG at county and national scale; (b) analyze the spatial patterns in ILYG across regions with significant prevalence of irrigation (c) determine and interpret the temporal trends in ILYG over multi-decadal periods; and (d) characterize the interannual variability in ILYG across vast and variable production conditions for major US crops. These crops include maize (Zea mays), soybean (Glycine max), spring wheat (Triticum spelta), winter wheat (Triticum aestivum), alfalfa (Medicago sativa), sorghum (Sorghum bicolor), cotton (Gossypium), barley (Hordeum vulgare) and oats (Avena sativa). To the best of our knowledge, there has not been a comprehensive study of quantitatively addressing ILYG at an appropriately fine scale, the spatial distribution of these differences, and the evolution of ILYG over time. By investigating these, our overall goal is to understand the outcomes of historical irrigation development, adoption, and management efforts in the United States to evaluate the regions for their long-term performance in employing irrigation to improve crop yields against rainfed crop yields. This will also assist ongoing yield gap research efforts by expanding our knowledge base on the yield penalties and uncertainty (risk) that producers are incurring rainfed agriculture relative to irrigated agriculture. Moreover, we also investigate if historical irrigation expansion and adoption has been more focused and/or efficient in improving yields for certain crops than others, and if so, buy how much. This study provides an assessment of ILYG in a spatiotemporal manner so that underperforming regions can be identified and efforts to invest in irrigation technologies can be directed to enhance overall national productivity.

Materials and methods

Data source and pre-processing
Irrigated and rainfed yield data for maize, soybean, spring wheat, winter wheat, alfalfa, sorghum, cotton, barley and oats were obtained from National Agricultural Statistics Service, United States Department of Agriculture [24]. These crops were selected so as to represent majority of the US agricultural output (crops selected account for 80% of the 2017 US harvested acreage). All the county-level yield records for each crop were retrieved from around 1950 (crop-specific) until the most recent records (2015). The data were subjected to certain degree of pre-processing prior to use. First, raw data were checked for missing records and temporal extents were decided for each crop type based on available records. Only those counties which had a minimum of 15 data records for both irrigated and rainfed yields were selected for analyses. supplementary table S1 lists the start, end, period of analysis and the number of counties that qualified the pre-processing criteria for inclusion in the study. Finally, yield values were converted to metric units (kg ha\(^{-1}\)) for each crop to maintain consistency.

Computation of irrigation-limited yield gaps
Irrigation-limited yield gaps were computed for each county by subtracting rainfed yield for a particular year from the corresponding irrigated yield:

\[
\text{ILYG}_{\text{county}, \text{year}} = \text{IY}_{\text{county}, \text{year}} - \text{RY}_{\text{county}, \text{year}}
\] (1)
where, ILYG is irrigation-limited yield gap (kg ha\(^{-1}\)), IY is irrigated yield (kg ha\(^{-1}\)) and RY is rainfed yield (kg ha\(^{-1}\)).

Further, a normalized metric was employed to represent ILYG for a county and year relative to rainfed yield for that particular county and year (Normalized ILYG). This was done to aid spatial and inter-crop comparison of ILYG. This index was computed as:

\[
\text{Normalized ILYG}_{\text{county, year}} = \frac{\text{IY}_{\text{county, year}} - \text{RY}_{\text{county, year}}}{\text{RY}_{\text{county, year}}}
\]

(2)

The long-term mean ILYG and normalized ILYG were computed for each studied county and each crop to present spatial patterns of these variables across geographical regions.

**Variability and trend analyses**

To discern and characterize trends and variability associated with ILYG for various crops, a range of statistical measures were computed. Linear regression of ILYG against time (year) was conducted to investigate the rate of change of ILYG, at both national and at county levels for each crop. Next, ILYG residuals from the fitted linear function were calculated, a modulus function was applied to the residual and a ratio was computed by dividing it by the predicted value derived from the linear fit. This resultant quantity was referred to as percent absolute deviation. Further, to investigate if the variability in ILYG has changed over time and in what fashion, a linear regression of percent absolute deviations against time (year) was conducted and county-specific rates of change for each crop were quantified. Statistical significance for the linear fit was also tested for each county at 95% and 90% confidence levels. The percent absolute deviations were averaged across the available records for a county to represent general long-term variability encountered in ILYG in that county. Fraction of years was computed in each county’s data record where percent deviations had certain properties, for example, positive, greater than +20%, and lower than −20%. Mean positive and negative percent deviations for each county and each crop were calculated. All of the above calculations were performed using scripts developed in RStudio version 1.1.423.

We mapped all the indicators and metrics quantified at county-level using ESRI ArcMap 10.4 for each crop to better understand the spatial patterns associated with them.

**Results**

**Irrigation-limited yield gaps: national patterns**

Overall, we find that producers have been experiencing substantial differences in crop yields when under irrigated versus rainfed management. To support our inference of these trends, we present nationally-averaged ILYG magnitudes (kg ha\(^{-1}\)) across major US crops, along with the historical standard deviation in ILYG (figure 1(a)). Maize demonstrated a long-term mean ILYG of about 4000 kg ha\(^{-1}\), which is about 35% of the mean 2016 US maize yield and the associated standard deviation (SD) indicates that it has historically been as high as 52% of mean 2016 US maize yield. The absolute magnitudes shown in figure 1(a) might not represent ILYG levels in a comparative way across all crops, due to very different levels of biomass and yield production (for instance, maize and cotton ILYG cannot be fairly compared in figure 1(a), owing to extreme levels of productivity). To resolve this, we normalized ILYG using crop-specific rainfed yield for fair comparison among each crop’s ILYG (figure 1(b)). Under this improved comparison, maize still demonstrated highest ILYG across all species (1.70 times the rainfed yield. Maize is followed by spring wheat and alfalfa and so on (figure 1(b)), while the lowest normalized ILYG is exhibited by soybean (0.7 times the rainfed yield). Overall, the nation has been experiencing ILYG as high as 2.7 times the rainfed yields (in maize) and as low as 0.25 times as rainfed yields (in winter wheat). Conclusively, this analysis informs us that irrigation leads to substantial yield advantage over rainfed production, which, on an average, can range from 0.7 to 1.7 times the rainfed yield, depending on the crop and location.

**Spatial changes in irrigation-limited yield gaps**

As previously observed in figure 1, national-level long-term mean ILYG is subject to large deviations around the mean magnitude. Such broader-level aggregation of information often tends to mask potential fine-scale spatial variation. Since crop yield data are collected and reported at finer (county) scale using surveys, census etc, their aggregation on national scale conceals any finer scale spatial dynamics. Hence, it is necessary and appropriate to study ILYG at county scale, in conjunction to national-level analyses. Figure 2 presents the spatial distribution of county-scale absolute ILYG (kg ha\(^{-1}\)) for the corresponding crop growing regions. Considerable spatial variability exists in ILYG within the crop growing regions, which for example, varies seven folds for maize within 10 degrees of longitude. For the same reasons explained earlier, county-level normalized ILYG were also computed for each crop (figure 3). Regions that show highest magnitudes of normalized ILYG were identified,
such as eastern Colorado, southwest Kansas and southwest Nebraska (for maize), southern Idaho and Washington, western Utah (for wheat), Idaho and eastern Colorado (for alfalfa) etc. Since normalized ILYG can be compared across different crops, it can be evaluated if one crop has been historically demonstrating higher gaps than other crops in a region, on an average. For example, considering western Kansas, we find that normalized ILYG for maize is the highest (2.1–2.5), followed by sorghum (0.6–1.0) and winter wheat (0–0.5), which implies that crop-specific signatures exist for ILYG, even in the same geographical region.

Temporal patterns in irrigation-limited yield gaps

Since considerable variability and trends exist in irrigated and rainfed yields [12, 21] owing to genetic and technological advances, and improved crop and soil management and weather [add citations], it is anticipated that ILYG will inherit a conjunctive effect of these variability and trends. To study and evaluate these changes, we assimilated national-level ILYG for each year, and fit a linear function to the resulting ILYG data against time (figure 4). Except for sorghum (due to extensive interannual variability), all crops showed moderate to strong positive correlations of ILYG with time. In other words, the difference (gap) in irrigated and rainfed yields is shown to widen over time. The crop-specific slopes (kg ha$^{-1}$ yr$^{-1}$) of the linear functions signify the annual increment of ILYG in each successive year. While these are important statistics to understand absolute rate of change in ILYG, however, they cannot be used to aid in fair comparisons across various crops, as explained previously. Rather, to accomplish this, we relied on annual gain in ILYG as percent of long-term mean ILYG. We change in ILYG, however, they cannot be used to aid in fair comparisons across various crops, as explained

Figure 1. Nationally averaged (a) irrigation-limited yield gaps (ILYG) (kg ha$^{-1}$) and (b) normalized irrigation-limited yield gaps (ILYG) (fraction) for maize, soybean, spring wheat, winter wheat, alfalfa, cotton, sorghum, barley and oats. Each quantity represents a mean value across space (counties) and time (growing seasons). Figure 1(b) facilitates inter-comparison of irrigation-limited yield gaps across crops. Error bars represent the standard deviation associated with each quantity. The crop-specific data is presented in order of highest to lowest total national crop production (left to right) in the US.
Figure 2. Irrigation-limited yield gaps (kg ha$^{-1}$) for each corresponding crop growing US county for (A) maize; (B) soybean; (C) spring wheat; (D) winter wheat; (E) alfalfa; (F) cotton; (G) sorghum; (H) barley; and (I) oats. Each county-specific ILYG was averaged over a time-series of data points based on data availability. Only those counties are shown which had at least 15 data points in their records. The crop-specific data is presented in order of highest to lowest total national crop production (left to right) in the US. It should be noted that each map has a separate color legend for interpretation, and hence inter-comparison among various maps based on color should be avoided. We developed the maps using ESRI ArcMap 10.4.1 software (http://desktop.arcgis.com/en/arcmap/).
Characteristics of historical variability in irrigation-limited yield gaps

Long-term change in ILYG variability

There has been sufficient interest in studying changes in crop yield variability over long-term crop data records [11, 16, 27]. However, the mean variability and change in variability in the difference between irrigated and rainfed yields (ILYG) remains unknown. We used similar methods (indices and statistics) as Kucharik and Ramankutty (2005) [16], to investigate changes in ILYG variability for nine major US crops at county scale. We determined county-level slopes of the linear regression analysis performed on percent absolute deviations of ILYG from the fitted linear function against time (figure 6). It is evident that there is high spatial variability in the temporal rates of change in ILYG deviations (or variability). Regions with increasing ILYG variability (positive slope of ILYG deviations from linear fit) signify that the inter-dynamics of irrigated and rainfed yields have become more prone/susceptible to both management, and external influences of weather and climate. Counties with decreased ILYG variability (negative slope of ILYG deviations from linear fit), on the other hand, imply that the degree of susceptibility of ILYG to influencing factors has decreased in long-term. On a national basis, maize, winter wheat, sorghum and oats have historically shown an increased ILYG variability, while soybean, spring wheat, alfalfa, cotton and barley have shown a decreased ILYG variability (table 1). The rates of change in ILYG variability were tested for their statistical significance at both 90 and 95% significance level (supplementary figure S2). Significant slopes were found in around 20%–43% of the counties that were investigated. A majority of the statistically significant trends are ones which are positive (increasing variability); for example, positive slopes for Nebraska maize ILYG variability are significant throughout the state. Limiting our analysis to only statistically significant trends in ILYG variability, we find that soybean and alfalfa no longer demonstrate decreased variability, but rather show increased variability with time. Also, sorghum and oats demonstrate even greater increases in variability, when we limited our analyses to significant counties. The only major exception is cotton, for which decreasing ILYG variability is statistically significant in majority of Texas cotton-growing counties.
counties. Other regional exceptions exist, such as counties in Montana that showed decreasing variability for spring wheat, winter wheat, and barley. Overall, we infer that all crops, on a majority basis, showed significant increasing interannual variability in ILYG, except cotton, which implies greater susceptibility of relative performance of irrigated and rainfed yields.

Mean spatial patterns of ILYG variability
To characterize the historical mean geographical patterns of ILYG variability, county-level mean percent absolute deviation of ILYG for the given data records for each crop were presented (figure 7). The mean percent absolute variability ranges from a minimum of 8% to as high as 70% across all the crops and the spatial extent of the US cropland. We find that the areas with greater mean ILYG variability coincided with the ones with lower normalized ILYG (figure 3). The lowest variability was found in southeast Wyoming (for maize) and northeast Colorado (for maize and alfalfa). Likewise, some major regions of highest variability include eastern Dakotas (for maize, sorghum and oats), northern Montana (for wheat, barley and oats), and central Nebraska (for winter wheat). On a national average basis, cotton showed the greatest mean variability (50%), followed by winter wheat (42%), soybean, barley, and oats (all around 25%), sorghum and spring wheat (both 33%), and alfalfa and maize (both 25%).
Frequency of Positive ILYG Variability

Although the above analyses provide insights into long-term patterns of ILYG variability, yet it does not account for nature of that variability (positive/negative) as well as interannual distribution of the variability. We addressed these aspects of ILYG variability by presenting the percentage of years in county-level ILYG records that show positive ILYG deviation for each crop (supplementary figure S3). As explained previously, positive and negative ILYG variability means that the deviation (residual) of a growing season-specific ILYG from the long-term linear fit is either positive or negative, respectively. On a national basis, all crops showed similar percentage of years with positive ILYG deviation (47%-49%). However, for a given crop, significant spatial variability was observed across counties, with the proportion of years with positive ILYG variability ranging from 30 to 60%. Maize, soybean and sorghum show lower proportions (greener shades in figure S3) of years with positive ILYG variability in eastern and central Nebraska, which implies that this region has been experiencing primarily negative ILYG deviations for these crops. On the other hand, in western Nebraska, majority positive ILYG variability was found for maize ILYG. Overall, for all the crops, majority positive ILYG variability (>50%) in any crops’ yield record did not occur in more than 41% of the total counties. To be specific, majority positive ILYG variability was found in 32% (maize), 26% (soybean), 38% (spring wheat), 30% (winter wheat), 41% (alfalfa), 28% (cotton), 31% (sorghum), 39% (barley), 34% (oats) of the total counties studied. This concludes that historically, for all the crops, the difference in irrigated and rainfed yields was more frequently (for greater number of growing seasons) subjected to negative variability from the long-term linear fit.

**Positive versus negative ILYG variability**

Now that the frequency of the occurrence of positive/negative ILYG variability has been quantified, it is equally crucial to compare the magnitudes of each kind (positive/negative) of ILYG variability, as well. We computed the difference between county-level mean absolute positive and negative yield deviations for each crop (figure 8). Since it is calculated as positive minus negative mean absolute deviation, the gradient of red color shown in figure 8 represents counties where average negative deviations were greater in magnitude than their positive
counterparts, and gradient of green color denotes counties where the opposite is true. Overall, the US cropland shows average positive ILYG variability that has been as high as 50% greater than negative variability, as well as negative variability that has been as high as 30% greater than positive variability, in certain counties. On a national level, the difference between mean absolute positive and negative ILYG variability was positive for all crops, implying that magnitude of positive deviations was higher than negative deviations. Specifically, the difference was distantly greatest for cotton (22.44%), followed by winter wheat (7.33%), soybean (5.40%), oats (3.71%), barley (3.34%), sorghum (3.30%), maize (3.06%), spring wheat (2.94%), and alfalfa (0.90%). Cotton area was dominantly populated by greatest magnitudes of difference between mean absolute positive and negative ILYG deviations in Texas (figure 8(f)), which explains the highest mean value demonstrated by this state. Combining this with our previous inferences, we find that although negative ILYG variability has been more frequent for all crops, the magnitude of positive ILYG variability has been greater than negative ILYG variability. Thus, the difference in irrigated and rainfed yields for various crops has been subjected to more frequent—but-lower intensity negative interannual variability, and less frequent—but-higher intensity positive interannual variability.

**Frequency distribution of ILYG variability**

To observe the distribution of the long-term and large scale dataset of ILYG variability, frequency histograms were developed for each crop that show fraction of county-crop seasons (this was computed as a product of counties and crop seasons) that fall under different classes of percent variability (supplementary figure S4). Focusing on the four vertical lines that emphasize the four largest classes of variability, we find that all crops’ distribution peaked in the −20 to 0% variability category (with fractions ranging from 0.16 to 0.29), except spring wheat and winter wheat distribution, which peaked in the 0 to 20% variability category (fraction being around 0.22). Maize ILYG showed maximum proportion of data in the −20 to 0% category, followed by alfalfa, spring wheat, barley, sorghum, winter wheat, soybean, oats and cotton. Soybean demonstrated a higher fraction...
Table 1. Crop-specific national mean magnitudes of the various metrics employed in the study.

| Variable                                           | Unit                  | Maize | Soybean | Spring wheat | Winter wheat | Alfalfa | Cotton | Sorghum | Barley | Oats |
|----------------------------------------------------|-----------------------|-------|---------|--------------|--------------|---------|--------|---------|--------|------|
| Total counties included                           | NA                    | 251   | 146     | 190          | 407          | 224     | 107    | 254     | 218    | 96   |
| Percent data record available                     | %                     | 57    | 66      | 50           | 57           | 75      | 74     | 55      | 63     | 72   |
| ILYG                                               | Kg ha\(^{-1}\)        | 4119  | 1004    | 1682         | 1467         | 1866    | 289    | 2176    | 1556   | 925  |
| Normalized ILYG                                    | fraction (relative to rainfed yield) | 1.7   | 0.7     | 1.4          | 1.0          | 1.4     | 0.9    | 1.1     | 1.1    | 1.0  |
| Slope of ILYG                                      | Kg ha\(^{-1}\) yr\(^{-1}\) | 45    | 18      | 32           | 21           | 14      | 9      | –12     | 27     | 16   |
| Slope of ILYG relative to mean ILYG                | %                     | 0.9   | 1.6     | 1.9          | 1.2          | 0.8     | 2.9    | –0.6    | 1.8    | 1.8  |
| Slope of percent absolute deviation               | %                     | 0.3   | –0.1    | –0.1         | 0.1          | –0.1    | –1.6   | 0.6     | –0.2   | 0.1  |
| Percent counties with significant slope            | %                     | 43.4  | 35.6    | 32.1         | 25.1         | 20.5    | 26.2   | 25.6    | 26.6   | 35.4 |
| Mean absolute percent deviation                    | %                     | 24.4  | 36.4    | 32.0         | 41.7         | 25.5    | 50.3   | 33.1    | 36.9   | 37.6 |
| Percentage years with positive deviation           | %                     | 47    | 47      | 49           | 48           | 49      | 47     | 49      | 49     | 48   |
| Difference of average absolute positive and negative deviation | %     | 3.1   | 5.4     | 2.9          | 7.3          | 0.9     | 22.4   | 3.3     | 3.3    | 3.7  |
| Percentage years with positive extreme ILYG variability | %     | 22.5  | 31.1    | 26.6         | 30.3         | 23.8    | 32.6   | 29.1    | 27.5   | 31.2 |
| Percentage years with negative extreme ILYG variability | %     | 23.9  | 34.4    | 28.5         | 33.0         | 25.0    | 36.9   | 31.5    | 30.0   | 33.9 |
of county-crop seasons in −40% to −20% category than 0 to 20% category. These frequency distribution functions provide an opportunity to study the variability dynamics of ILYG at the most fundamental unit possible: county-crop seasons, which is not subjected to any aggregation or averaging.

**Extreme ILYG variability**

Extreme weather detrimentally affects regional [28–30] and global [31] crop yields. Extreme weather effects, especially extreme precipitation, can be anticipated to cause consequent effects on ILYG, because of high vulnerability of rainfed crop yields to precipitation [21]. In this context, it is important to characterize the extreme variability in ILYG. Any variability (in percent deviation) that is beyond 20% magnitude (whether positive or negative), has been categorized as extreme ILYG variability in this research. Extreme ILYG variability can result for growing seasons that witness substantial environmental variability such as precipitation extremes that either positively or negatively impact rainfed yields. For example, drought conditions and extremely wet conditions can result in severe soil water deficits and late planting and/or drainage issues, respectively. These environmental conditions affect rainfed crop productivity, primarily, but can also impact irrigated crop productivity, or both. Depending on the relative degree of impacts on rainfed and irrigated yields, extreme variability is caused in ILYG. We computed the percentage of years in county-level ILYG records, which showed deviations from the fitted linear function that were greater than 20% and lower than −20% for each crop, respectively (supplementary figures S5 and S6). These percentages vary from 0 to as high as 60%. A substantial area shows a value of 31%–40% (lighter pink in figures S5 and S6) such as eastern Kansas (for maize), central Nebraska (for soybean), Montana (for spring wheat), the Great Plains (for winter wheat), eastern Nebraska (for alfalfa), Texas (for cotton), western US (for barley), and Montana (for oats). This essentially implies that these areas experience extreme ILYG variability (>20% or −20%) for 3–4 times every decade, on an average. Other areas are more resilient against extreme variability causes, such as western Central Plains (for maize and alfalfa),

![Figure 7](http://desktop.arcgis.com/en/arcmap/).
Utah and southeastern Idaho (for barley), which experience extreme ILYG variability for once every decade, on an average. It is noteworthy that regions of extreme variability, either positive or negative, almost totally coincide with each other. Also, we observe that cotton experienced the highest occurrence of positive and negative extreme ILYG variability, followed by soybean, winter wheat and oats, with the least extreme occurrence was observed for maize and alfalfa.

**Discussion**

Our research comprehensively quantified and studied several metrics to characterize ILYG in order to benchmark the dynamics of the crop yield improvement resulting from irrigation relative to rainfed production. ILYG was found to be site-specific as well as crop-specific. maize showed the greatest ILYG on a national basis. National-level ILYG has been increasing at varying rates for different crops and regions since the 1950’s, with cotton ILYG showing the highest rates of increase. Spatial patterns of ILYG are inversely proportional to the precipitation patterns. Increased ILYG variability over the study period was found for all crops, except cotton, which also showed the highest magnitude of long-term mean variability. Negative deviations in ILYG occurred more frequently, especially in cotton and soybean. However, the magnitude of less-frequent positive ILYG deviations was higher than negative ILYG deviations. Magnitude of positive deviations relative to negative deviations as well as extreme variability was highest for cotton. The spatial patterns of extreme ILYG variability were identified and it was found that extreme ILYG variability occurs as frequently as 3–4 times per decade.
ILYG versus precipitation
We suggest that long-term spatial patterns observed in ILYG are governed by the precipitation received in the crop growing season. Regions with higher precipitation show lower ILYG and vice-versa. Since irrigated crop production at a site is generally not water-limited (exceptions exist in western US), its yield is normally not constrained by the precipitation it receives. On the other hand, rainfed yields are a strong function of precipitation amount, resulting in low ILYG in regions which receive enough or close to enough precipitation to produce yields that are closer to irrigated yields. Growing season precipitation (May 1st until September 30th) increases three folds from western to eastern Nebraska [32]. There exists a west–east decreasing pattern in ILYG in Nebraska (figure 2), which correlates with west–east increasing patterns in seasonal precipitation amount. A smooth spatial pattern of precipitation is the reason that almost all the metrics discussed show a recognizable spatial west–east pattern in Nebraska, unlike other states. This is also true for the states to the east of Nebraska, whereas western US lacks this longitudinal signature where precipitation is largely orographic, governed by topographical features rather than longitudinal variation.

To demonstrate the inverse relationship of ILYG with growing season precipitation at a fixed location, a meta-analysis was performed using field experimental research data [33–37] (maize-based) from the Irmak Research Laboratory at South Central Agricultural Laboratory (Clay County), Nebraska (figure 9(a)). The results were similar to what we observed when we investigated the response of long-term mean ILYG with long-term mean growing season precipitation for maize-producing counties in Nebraska (figure 9(b)), which showed that the precipitation and ILYG are correlated on a spatial scale, as well. A better qualified index that could be investigated for its role in driving ILYG is the deficit of crop evapotranspiration (ETc) and precipitation. However, since it is challenging to estimate ETc at large spatial and temporal scales [38] for all the crops included in this research, this exercise is beyond the scope of this research.

Figure 9. (A) Maize ILYG versus growing season precipitation using meta-analysis conducted at South Central Agricultural Laboratory, Clay Center, Nebraska; (B) long-term mean maize ILYG versus growing season precipitation across Nebraskan counties; (C) long-term mean maize normalized ILYG versus growing season precipitation across Nebraskan counties; (D) long-term mean absolute percent deviation in maize ILYG versus growing season precipitation across Nebraska counties.
Normalizing ILYG
ILYG was normalized using rainfed yield to be employed to decipher spatial trends among vast geographical regions and crops. This is justified because of geographical differences in crop productivity in different agroclimatic zones, which govern the maximum attainable yield potential. For example, regions such as Dakotas have been observed to have lower mean yields than central Nebraska [20] due to inherent differences in agroclimatic indices such as heat accumulation and growing season length [39]. ILYG computed at these sites may be biased by disparities in mean yields at these sites and thus, it is not fair to compare ILYG across spatial domains, necessitating normalization of ILYG. The normalized ILYG was better able to explain the inverse relationship with growing season precipitation (figure 9(c)), as it was a stronger function of precipitation than absolute ILYG (coefficient of determination ($R^2$) increased by about 18% from 0.60 to 0.73). Another observation that lends strength to our normalization strategy is that the $R^2$ magnitude following the linear trend is approximately equal to the one obtained from the site-specific meta-analysis (figure 9(a)).

Interpreting changes in ILYG
Spatial changes in ILYG that have been demonstrated in this analyses represent differences in crop response to availability versus non-availability of irrigation water in geographically and temporally varying agro-ecosystems. The regions of greater ILYG have substantial potential to increase their rainfed production via moisture conservation, soil management, technological measures, and other practices. Similarly, regions of lower ILYG are producing relatively comparable yields under irrigated and rainfed settings, which imply that irrigation practices are not critically crucial here. Additionally, from an irrigation-development point of view, a larger ILYG demonstrates that the returns of irrigation development efforts have been maximal, which is a desirable scenario. These regions, in most cases, experience greater atmospheric evaporative demands, which are only sufficiently met by irrigation. Rainfed crop production, on the other hand, yield sub-optimally due to detrimental impact(s) of water and heat stress on plant carbon assimilation processes. Another factor that might be responsible for spatial differences in crop ILYG is the distribution and length of crop growing seasons [39]. These indirectly influence the effective precipitation received by the crop (based on precipitation seasonality), and hence impact ILYG, by causing fluctuations in rainfed yields, primarily. For instance, the dissimilarities in growing seasons of maize (April–November), sorghum (May–November), and winter wheat (September–July) in the US lead to different wetness regimes experienced by the crops, which is further amplified by extensive geographical variation in planting and harvesting dates for a given crop [40].

Temporal trends in ILYG signify equally important implications for the US cropland. Firstly, it is inferred that irrigated yields have been improving at a greater rate than rainfed yields, evident from the positive slopes of ILYG over time (figure 4). The greater rates of improvement in irrigated than rainfed yields are an effect of adoption of more efficient sprinkler-based center pivot irrigation systems and micro irrigation technologies like surface and sub-surface drip (although less extensively in comparison to center-pivot irrigation), superseding furrow/flood irrigation systems. Secondly, the ILYG widening trend varies by crop and location, showing that not all crops and regions are equally effective at exploiting the availability of irrigation to increase productivity. The negative trends in temporal ILYG imply that the additional yield advantage achieved with irrigation is decreasing. A major cause of this ILYG narrowing trend might be stagnation of irrigated yields in recent years [41]. Whilst irrigated yields can plateau, being closer to their biophysical limits, rainfed yields can continue to improve, especially in instances of increased seasonal precipitation and uniform precipitation distribution during the growing season, reducing the potential for water stress. It has been shown that maize and soybean growing seasons have been getting wetter in the US Great Plains [42], benefitting rainfed yields. Moreover, increased adoption of conservation agriculture practices such as no or reduced tillage in recent years might also have a beneficial impact on moisture storage for maintaining rainfed yields [43, 44], at least in drier locations and years.

Interpreting changes in ILYG variability
The patterns of ILYG variability were shown to be explained by interannual variability associated with the growing season precipitation for each crop. In a region where growing season precipitation variability is higher, the rainfed yields will demonstrate greater variability while irrigated yields will be able to effectively mitigate the precipitation changes, explaining the higher mean ILYG variability in that region. Thus, the inter-crop differences in ILYG variability may be explained by distribution of cropping regions with respect to regions of greater precipitation variability. The interannual frequency distributions of positive deviations were mapped for US croplands (supplementary figure S4), but it was challenging to discern a uniform pattern, unlike other indicators. This was anticipated given the heterogeneity of crop growing seasons as well as precipitation distribution. Positive ILYG deviations translate to rainfed yields being lower than expected (from linear trend),
while negative deviations translate to rainfed yields being higher than expected, provided that irrigated yield variability are minor, at least relative to that in rainfed yields. Irrigated yield variability, although minor, can be a result of drying wells and declining water availability, especially in parts of California Central Valley and High Plains [45–47]. Nevertheless, the maps presented here can be interpreted to evaluate whether rainfall yields perform better or worse than expected. Similarly, a positive extreme ILYG deviation (>20%) indicates a sharp decline in rainfed yields, whereas a negative extreme ILYG deviation (<−20%) indicates an unusual increase in rainfed yields. Thus, in a holistic sense of the overall agricultural output, negative extreme ILYG deviations might be beneficial/desirable.

Significance

The findings and resources (maps) presented in this study can be instrumental to carry out several assessments that relate to agricultural irrigation policy and optimization of cropland productivity on large scales. These can used to develop effective and scientifically-based decision-making for enhancement of national agricultural productivity in the light of changing environmental conditions that undoubtedly crop yields. Firstly, county-specific ILYG magnitudes can be consulted to aid potential producers and other stakeholders in decisions related to conversion of rainfed to irrigated production, when feasible, to realize the yield and economic advantage associated with the conversion. Conversely, these results can also be valuable for quantifying agricultural productivity impacts of water rights trades, especially in the western US, where evidence suggests that water rights have been and are projected to be reallocated from lower-valued agriculture to higher-valued urban uses [48, 49]. This trade results in low water availability for agricultural production, and hence in severe cases, conversion of irrigated crop production to rainfed production, rangeland, or conservation/wildlife habitat. Our research has quantified multi-year, multi-crop crop productivity differences in irrigated and rainfed agriculture for the entire US, which can be used to determine the economic impact (ranging from farm, county, state and national levels) associated with this conversion. Provided that all the regions can be characterized in terms of cultivars that are generally prevalent in them, plant breeders and geneticists can attempt to selectively carry out technological advancements in crop cultivars, hybrids and varieties which consistently show greater ILYG. Additionally, regions and crops with higher ILYG can be identified for focused development in moisture conservation through conservation agriculture and other key agronomic practices to increase rainfed productivity.

Since very recently, policymakers have been debating imposition of irrigation water pumping allocations in regions with severe groundwater depletion. These allocations may or may not be sufficient to meet crop water requirements [50], especially in extreme years (in terms of precipitation and evaporative demand). Our analysis can contribute to achieve greater scientific soundness in this policy-development. We recommend that allocations be imposed in regions where the ILYG has been shown to be lower and regions which grow crops that have shown lower ILYG in our analysis. The foundational basis for this claim being that if the allocations are insufficient for certain years, the rainfed (or deficit-irrigated) yields will demonstrate relatively greater resilience in regions and crops with long-term tendencies of higher ILYG (figure 2). Quantitative rates of change in ILYG as well its variability can be beneficial in deciphering the impact of historical trends of irrigation adoption and policy implementation on the dynamics of the yield advantage and its robustness against inter-annual environmental variability. Crops can be assessed for their future potential for irrigation management research and development, as well as their success in regions of water rights trades and transfers to urban sector, based on the historical patterns and projections of ILYG temporal trends quantified here. Finally, our study presents an unprecedented detail and inclusiveness in terms of crops (nine major crops) and the regions (complete US cropland) studied. This allows the concerned personnel and policy- and decision-makers to compare and contrast large-scale cropland production dynamics efficiently.

Limitations

We have also identified a few limitations with the approaches adopted in this study. Firstly, this research is based on USDA-NASS county-level crop yield data, which has its own discrepancies, one of them being incomplete and inconsistent data records. We chose the start and end of the study period for each crop depending on the data records available, hence these periods differ for all crops (supplementary table S1). Even within a crop database, the start and end periods differ by various states. Thus, we limited our analyses to counties which had at least 15 data records in order to have an acceptable number of data points to draw conclusions from. supplementary figure S7 describes the data availability for each county and crop, by showing the fraction of yield records available. We recommend that users are aware of these details when extracting information for their counties of interest. Secondly, we assume that irrigated and rainfed fields only differ by their irrigation management (i.e., presence or absence of irrigation). This may or may not be true in practice as the two management regimes may also differ by crop cultivars/hybrids, depending on their drought-tolerance
Principal Investigator, Dr Suat Irmak, expresses his appreciation to USDA-NIFA, NET, and CPNRD.

The authors declare no competing interests.

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Additional information: competing interests

The authors declare no competing interests.

Author contributions

M K and S I conceptualized the study and contributed to discussions and interpretation of the results. M K drafted the first version of the manuscript and S I conducted detailed review and revisions. M K compiled datasets and created figures in close consultation and discussions with S I.

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