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To cite this article: T Foster *et al* 2019 *Environ. Res. Lett.* **14** 024004

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Environmental Research Letters



LETTER

OPEN ACCESS

RECEIVED

15 September 2018

REVISED

30 October 2018

ACCEPTED FOR PUBLICATION

21 November 2018

PUBLISHED

25 January 2019

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Assessing landscape scale heterogeneity in irrigation water use with remote sensing and *in situ* monitoring

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Abstract

Understanding how irrigation is used across agricultural landscapes is essential to support efforts to grow more food while reducing pressures on limited freshwater resources. However, to date, few studies have analyzed the underlying spatial and temporal variability in farmers' individual water use decisions at a landscape scale. We compare estimates of irrigation water requirements derived using state-of-the-art remote sensing models with metered abstraction records for 1400 fields over a 13 year period in the US state of Nebraska, one of the world's most intensively irrigated agricultural regions. We show that farmers' observed water use decisions often diverge significantly from biophysical estimates of crop irrigation requirements. In particular, our findings are consistent with widespread use of water conservation practices by farmers in drought years as an adaptive response to rising irrigation costs and regulatory water supply constraints in these years. We also demonstrate that, in any individual year, farmers observed water use exhibits large field-to-field variability, which cannot be explained fully by differences in weather, soil type, crop choice, or technology. Our results highlight the value of using both *in situ* monitoring and remote sensing to evaluate farmers' individual water use behavior and understand likely responses to future changes in climate or water policy. Moreover, our findings also demonstrate potential challenges for current efforts in developed and developing countries to apply model-based approaches for field-level water use accounting and enforcement of irrigation water rights.

1. Introduction

As the largest consumer of water globally, agriculture is both sensitive to water scarcity and a major driver of inter-sectoral water conflict. Understanding how farmers use irrigation to mitigate drought risk therefore is essential to support long-term food security and to help to balance competing demands for limited water resources.

Water balance and crop growth models have been widely utilized for several decades to quantify irrigation water requirements as a function of agronomic, soil, and climatic conditions, and inform decision-making about irrigation water management at field-to-landscape scales [1–4]. More recently, research has

demonstrated the potential for remote sensing to support efforts to model the spatial and temporal variability in crop irrigation demands, for example through provision of satellite-derived information about field-level crop development or evapotranspiration [5–7] and irrigated areas [8–11]. Model-based assessments of irrigation water use provide estimates of the variability in irrigation water requirements due to biophysical factors such as weather, soil type, and crop choice. However, in addition to these biophysical drivers, farmers actual irrigation decision-making may also be influenced by a variety of other factors. These include physical or regulatory limits to available water and individual farm management strategies, which reflect underlying economic and social conditions (e.g. crop

and input prices, labor availability), and behavioral choices and uncertainty (e.g. risk aversion, irrigation heuristics).

Evaluating the differences between remotely sensed estimates of irrigation requirements and farmers actual water use would provide an opportunity to understand the importance of biophysical and behavioral factors to observed water use decisions. Unfortunately, due to the social and political difficulties associated with *in situ* monitoring of agricultural water use, there are almost no datasets that measure farmers actual water use decisions at field scales. Indeed, only 30% of irrigation wells in the United States are equipped with a flow meter [12]. Moreover, in many irrigated regions, agricultural groundwater pumping remains unmetered despite reductions in aquifer storage [13, 14] that threaten long-term agricultural productivity and sustainability of rural economies [15, 16].

In this study, we compare remotely sensed estimates of crop irrigation requirements and *in situ* observations of agricultural water use for over 9000 fields in the US state of Nebraska, one of the worlds most intensively irrigated agricultural regions. Our analysis seeks to evaluate the biophysical and behavioral drivers of farmers individual irrigation behavior over both space and time, and to understand to what extent remote sensing based water balance models can reconstruct reliably observed heterogeneity in field-level applied irrigation water use. Our results show that farmers observed water use decisions are less responsive to interannual weather variability than crop water requirements estimated using remote sensing. We provide empirical evidence for the use of deficit irrigation practices by farmers as an adaptation to drought at landscape scale. Furthermore, we demonstrate that large individual differences exist in individual irrigator behavior at field scales that are not related to weather, soil type, cropping decisions, or irrigation technology. Our findings demonstrate the value of combining remote sensing and *in situ* monitoring for understanding and predicting field-level irrigation water use practices, and highlight important challenges for use model-based approaches for agricultural water use accounting in the absence of *in situ* monitoring.

2. Methods and datasets

The following subsections describe the methods and datasets used to evaluate differences between *in situ* observed irrigation water use and remotely sensed estimates of crop irrigation requirements. Our study area is the Upper Republican Natural Resources District (URNRD) overlying the High Plains Aquifer in the US state of Nebraska. The URNRD is characterized by commodity cropping, primarily corn, that is irrigated using groundwater-fed center-pivot irrigation systems, typical of production on more than

7 million acres across the High Plains region [17]. More broadly, center-pivot systems irrigate approximately 80% of the total irrigated area in the United States [12], highlighting the importance of understanding water use behavior in these systems for regional and national agricultural water management.

2.1. Observed irrigation water use datasets

Observed field-level irrigation water use data were obtained from historical (2000–2012) pumping records for a total of 3337 currently active irrigation wells located within the URNRD in SW Nebraska. The period 2000–2012 was selected based on availability of quality-controlled metered irrigation pumping data from the URNRD, and, importantly, captures the full range of climatic conditions observed in Nebraska ranging from extreme drought (e.g. 2012) to years with significantly above average rainfall (e.g. 2011). For each well, annual irrigation rates were obtained from flow meter records, which are collected and verified annually by URNRD staff. Data are also reported about the crop grown and field area irrigated in each year, along with geospatial information about the location of the field. To the best of our knowledge, these data are one of the most comprehensive observations of producer-level irrigation worldwide.

2.2. Matching of irrigation wells and fields

Well-level irrigation records were matched spatially to locations of active center-pivot irrigation systems previously mapped using using fine-resolution Landsat 5 (30 m resolution) and Ortho imagery (1–2 m resolution) [18]. Center-pivots were identified where only one active irrigation well is located within the boundary of the field, and all remaining pivots were discarded to remove fields where a single source of pumping was not easily identifiable. Remaining pivot-well pairs were sub-sampled to identify combinations where both the (i) certified irrigated area for the well and (ii) physical area of the field are between 48.6 and 55.7 ha, and do not differ by more than 5%. Lower and upper area bounds capture quarter-section pivot-irrigated fields, the modal field size in the region that typically is irrigated using a single well thus ensuring that outliers are removed where well-field combinations may not be unique. The resulting matched pivot-well dataset contains a total of 1400 individual data points distributed across the URNRD (figure 1). Annual irrigation rates for each pivot are assumed to equal reported pumping rates given by the associated well meter record, reflecting that groundwater is the sole source of water for irrigation in the URNRD and there is no conjunctive use of surface water unlike in other important agricultural regions of the United States (e.g. California's Central Valley) [19].

2.3. Modeling crop irrigation water requirements

Model of estimates of irrigation water requirements, which provide a theoretical benchmark for how much irrigation would be needed to meet fully crop water demands for a given field and year, were simulated using a remote sensing driven water balance model. First, regular observations (approximately every 7–8 d) of the soil adjusted vegetation index (SAVI) were obtained from Landsat 5 TM and 7 ETM+ imagery between 1 April and 31 October each year. The time interval between SAVI observations reflects the typical revisit periods of Landsat 5 and 7 satellites, along with the presence of overlapping swaths in our study region that effectively double the frequency of image observation (8 d versus standard revisit period of 16 d for each satellite). Discrete SAVI values were interpolated to daily time series as a function of accumulated growing degree days as proposed by [20] and described in the online supplementary materials (stacks.iop.org/ERL/14/024004/mmedia) (section S1.1). Next, interpolated daily SAVI values were used to estimate the temporal evolution of the basal crop coefficient, K_{cb} , for each pivot and season using the functional relationship given in equation (1), which has been shown to capture accurately the temporal evolution of K_{cb} for high-yielding corn hybrids grown in Nebraska [20]

$$K_{cb} = 1.414 * (\text{SAVI} - 0.02). \quad (1)$$

Subsequently, K_{cb} time series were used as inputs to a soil water balance model to simulate daily actual crop evapotranspiration and irrigation water use for each field and year. The soil water balance model tracks daily changes in soil water storage as a function of inflows from effective rainfall and irrigation, and outflows from deep percolation and actual evapotranspiration. The model is based on the widely used and documented FAO-56 methodology [21], and, therefore, we provide only a brief description of key calculations and assumptions here (see online supplementary materials section S1.2 for a complete description of the model).

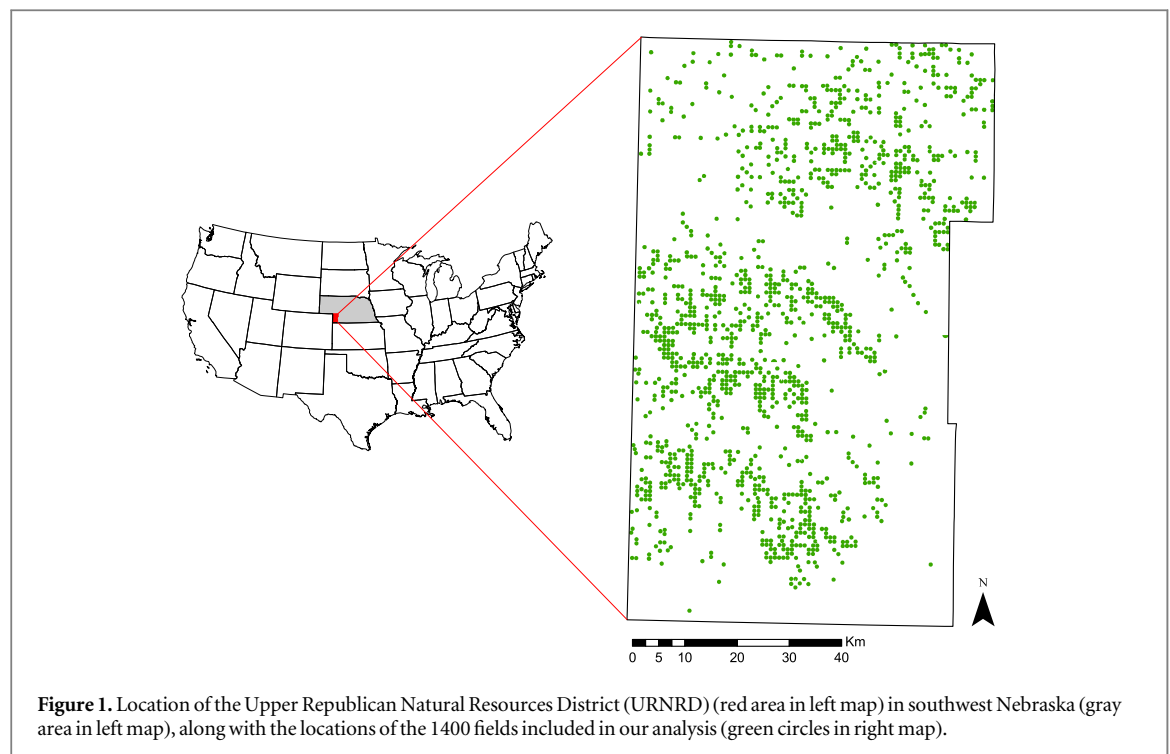
The soil water balance model estimates daily actual evapotranspiration and irrigation water application rates using the dual crop coefficient approach [21], given estimates of the basal crop coefficient (K_{cb}) estimated previously from SAVI estimates derived from Landsat imagery. Our prior research [20] has shown that this water balance model is able to simulate accurately patterns of daily actual crop evapotranspiration, which are a key driver of irrigation water requirements, for typical corn hybrids grown in Nebraska and the High Plains more broadly. Each model simulation begins at the start of the fallow period (31 October) in the previous year, and runs on a daily time-step until latest end of the simulated growing season (30 October). Irrigation is triggered on any day when cumulative soil water depletion is greater than or equal to a specified proportion, p , of the soil available water holding capacity (AWHC) for that field. The value of p

is set equal to 0.55 consistent with the onset of water stress conditions for corn [20, 21]. When triggered, the amount of irrigation applied is equal to that needed to refill the soil root zone to field capacity, subject to minimum and maximum application depths per event of 6.35 mm (0.25 inch) and 31.75 mm (1.25 in), respectively. It is assumed that each irrigation event has an efficiency of 90%, and that a 31.75 mm event will require 5 d to complete a full pivot rotation resulting in a maximum interval between irrigation events of 1–5 d. Each of these assumptions reflects the typical characteristics of center-pivot irrigation systems operating on quarter-section field sizes in Nebraska. Importantly, we also specify that irrigation will not occur (irrespective of soil water status) until K_{cb} exceeds a value of 0.2, indicative of the start of crop development after emergence, and will cease once K_{cb} declines below 0.4 as at this point the crop has reached physiological maturity. Consequently, simulations account for variability in the irrigation season duration between fields/years (e.g. due to planting date, variety, etc), with an average start date of mid-May and end date of mid-September.

Soil properties used to define the AWHC for each field are obtained from [22], considering an area-weighted average of all soil classes found within the pivot over the maximum crop rooting depth (1.5 m). Initial soil water depletion at the start of the fallow period in the previous year is set equal 50% of soil water holding capacity consistent with recommended best practice for modeling crop irrigation requirements in our study region in the absence of soil moisture observation data [23]. Daily K_{cb} values during the fallow period are set equal to 0.12 following values reported for experimental corn fields in Nebraska [20] and elsewhere [21, 24], and reflects evidence that a residual value of the basal crop coefficient should be considered to estimate accurately evapotranspiration under bare soil conditions [20, 25]. Finally, daily reference evapotranspiration (ET_0) is calculated using the ASCE Penman–Monteith equation, given observations of daily maximum and minimum temperature, solar radiation, and vapor pressure at 1 km² resolution from Daymet [26], which also provides records of total daily precipitation used as an input to our soil water balance model.

2.4. Comparison of actual and modeled irrigation use

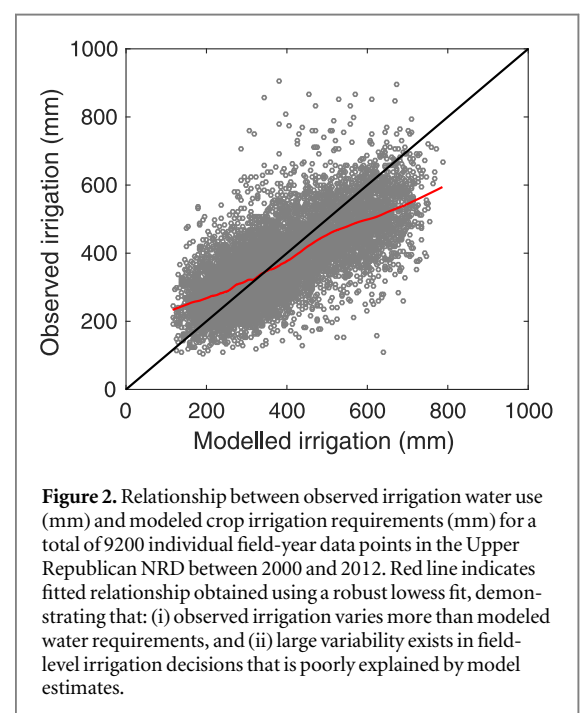
We focus comparison of actual and modeled irrigation water use on fields growing corn, the main irrigated crop in our study region. URNRD records [27] identify the crop grown on each field (corn accounts for 63%–79% of matched fields each year between 2000–2012), but do not state whether the full field was cropped. To avoid introducing errors to model estimates of irrigation water use, we remove fields from our analysis where evidence of fallow land was detected based on



supervised classification of SAVI values obtained from imagery at the time of peak crop development. Fields were discarded from the analysis where supervised classification identified that more than 5% of pixels within the field area were classified as non-vegetated, given indicative SAVI values for bare soil (0.12) and corn at full cover (0.68) used to train classification algorithms. Each field area was covered by multiple SAVI pixels (each with a resolution of 30m square), and the total number of SAVI observation points ranged from approximately 540–630 pixels depending on the individual field size. Discrete SAVI values for each field and image observation date were calculated by taking the area-weighted average of all pixels that intersected with the field area. Additionally, we also remove fields from our analysis where, in any given year, there were an insufficient number or frequency of cloud-free Landsat images to accurately interpolate daily SAVI curves, considering a minimum r^2 value for interpolated curves of 0.8 [20]. In total, our final analysis retains between 417–902 field-level records of observed and actual irrigation water use in each year (708 fields yr^{-1} on average) as summarized in table S1. Figure 1 shows the location of each of the 1400 fields included in our final sample, together with the location of the URNRD in southwest Nebraska.

3. Results and discussion

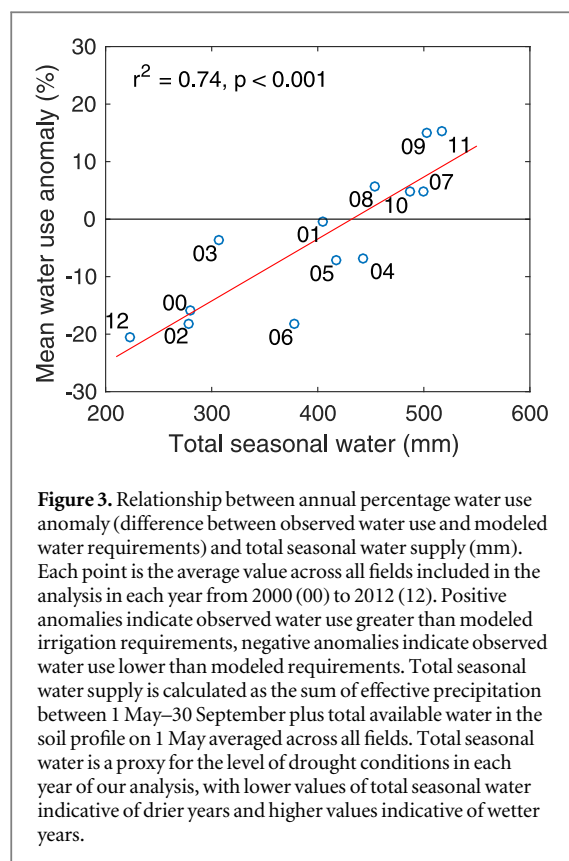
Figure 2 shows the differences between remotely sensed estimates of crop water requirements and metered groundwater irrigation records for a total of 9200 field-year data points over the period 2000–2012. The results demonstrate that there is large scatter in



the relationship between observed water use and remote sensing derived crop water requirements, from which several key insights emerge about farmers field-level irrigation decision-making.

3.1. Mean observed irrigation water use varies less over time than model estimates of biophysical crop water requirements

Figure 3 shows that the average annual difference between observed water use and crop irrigation requirements (the water use anomaly) is correlated strongly ($p < 0.001$, $r^2 = 0.74$) with total water

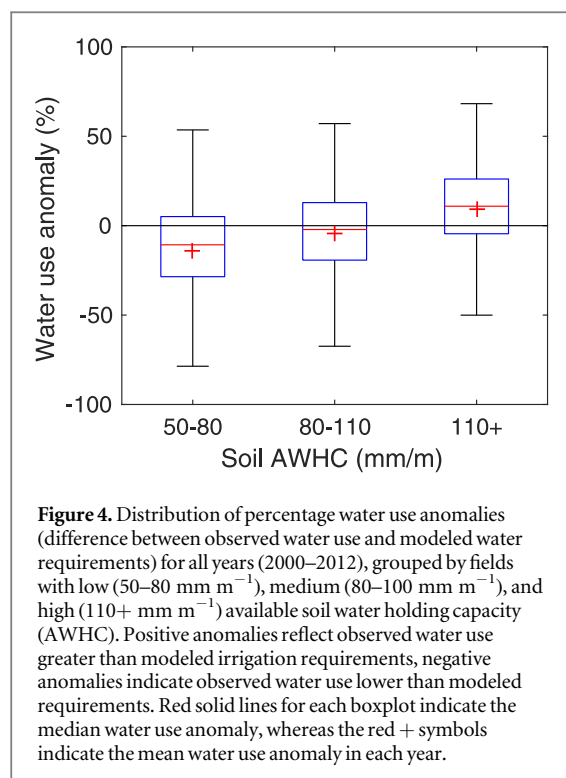


supply from seasonal precipitation and soil moisture at planting. In the wettest years of our record (e.g. 2011), we find that observed water use is on average equal to or greater than crop irrigation requirements. In contrast, in the driest years (e.g. 2012), observed water use typically is lower than crop water requirements. Trends across wet and dry years are further illustrated by scatter plots of observed versus modeled water use for each individual year of our analysis (figure S2), which show that the majority of fields fall above the 1:1 line (positive irrigation anomaly) in wet years and below the 1:1 line (negative irrigation anomaly) in dry years. These patterns indicate that, while both observed water use and modeled irrigation requirements vary over time at field-levels (figures S3(b) and S3(c)), model estimates of irrigation water requirements are statistically more responsive to interannual differences in weather conditions (precipitation and evapotranspiration demand) than actual water use decisions (table S2). Consequently, in wetter years we observe that farmers actual water use on average is greater than model estimates of biophysical water requirements, whereas in drought years farmers increasingly irrigate below full water requirements (deficit irrigation).

Several factors may explain the patterns in irrigation behavior observed in figure 2. First, increasing deficit irrigation in drought years could indicate physical constraints to groundwater pumping, for example due to low well yields [28]. However, for the most severe drought year in our analysis (2012), we find no

relationship between observed water use, or the size of the irrigation anomaly, and the reported well yield for each field (figure S5). This finding is consistent with the observation that the majority of wells in our study area have large capacities (figure S6), with yields averaging $5040 \text{ m}^3 \text{ d}^{-1}$, that allow farmers to increase water use freely in response to higher crop water demands during droughts. With the exception of a small minority of fields, physical well yield constraints therefore are unlikely to explain observed patterns of deficit irrigation in drought years. Similarly, while groundwater use in our study region is restricted as part of the multi-state Republican River Compact Agreement [29], allocations allow flexibility in water use across years conditional on total water use over each 5 year period not exceeding 65 inches (1561 mm) [30]. As a result, >98% of fields in 2012 pumped more than the average annual allocation of 13 inches (330 mm) while still maintaining regulatory compliance, with average pumping exceeding 20 inches (508 mm) (figure S3b). Moreover, regulations also allow farmers to bank unused water from historic allocation periods, increasing substantially the total 5 year cap on pumping for most fields and relaxing policy constraints to irrigation decision-making (figure S7).

We suggest instead that the divergence between observed water use and crop irrigation requirements in figure 3 is due to shifts in farmers irrigation decision-making as a function of seasonal weather conditions. In wetter years, water availability is plentiful for most farmers and, as a result, there are few incentives for producers to manage irrigation efficiently. However, in drought years, higher total pumping costs and perceived concerns about exceeding water use allocations may incentivize farmers to reduce water use even in the absence of binding physical constraints. These reductions could be achieved through adjustments to irrigation scheduling practices, such as reducing the number of volume of water applications during periods where the crop is less sensitive to water stress or through use of improved irrigation scheduling technologies (e.g. soil moisture probes, weather forecasts) that help to minimize non-consumptive losses (e.g. deep percolation) of applied water [31]. Alternatively, observed irrigation use patterns may instead reflect an underestimation by farmers of the magnitude of interannual changes in irrigation requirements. In the absence of additional information about farmers' irrigation scheduling (e.g. sub-seasonal water use data), it is not possible to verify the specific adaptations, deliberate or otherwise, adopted by farmers to minimize water use in drought years. However, we note that drought events show only a very weak correlation with irrigated crop yields in our study region and across Nebraska (table S3), with record yields reported in the major drought of 2012. This indicates that observed deficit irrigation during droughts on average has not resulted in large and systematic reductions in irrigated crop yields, consistent with evidence of minimal



binding physical or regulatory pumping constraints on average across our study region. Importantly, this finding suggests an increase in the efficiency and productivity of irrigated water use in drought years as a result of farmer-level adaptations to field-level irrigation decision-making. Conversely, our findings indicate that opportunities may exist to incentivize improved water management on fields in wetter years, and, in doing so, enhance producer profitability and support long-term groundwater conservation.

3.2. Producers whose fields have the lowest soil water holding capacity exhibit the largest responses to drought

Soil properties exhibit large heterogeneity across our study area (figure S8). Both observed irrigation water use and modeled irrigation requirements are greater on average for fields with coarser soils (397 mm and 435 mm, respectively) than on fields with finer soils (354 mm and 314 mm, respectively). However, we find that soil type also introduces unexpected differences in field-level irrigation behavior. Figure 4 shows that observed water use across all years is lower than crop irrigation requirements on fields with coarser soils (low AWHC), and greater than crop irrigation requirements on fields with finer soils (high AWHC). Similar trends are also observed when using data from only the wettest or driest years of our time series (figure S9). In all cases, differences in distributions across soil types are found to be statistically significant based on Mann–Whitney U tests ($p < 0.001$) (online supplementary materials, section S2.5). This suggests that irrigation practices may vary as a function of soil type

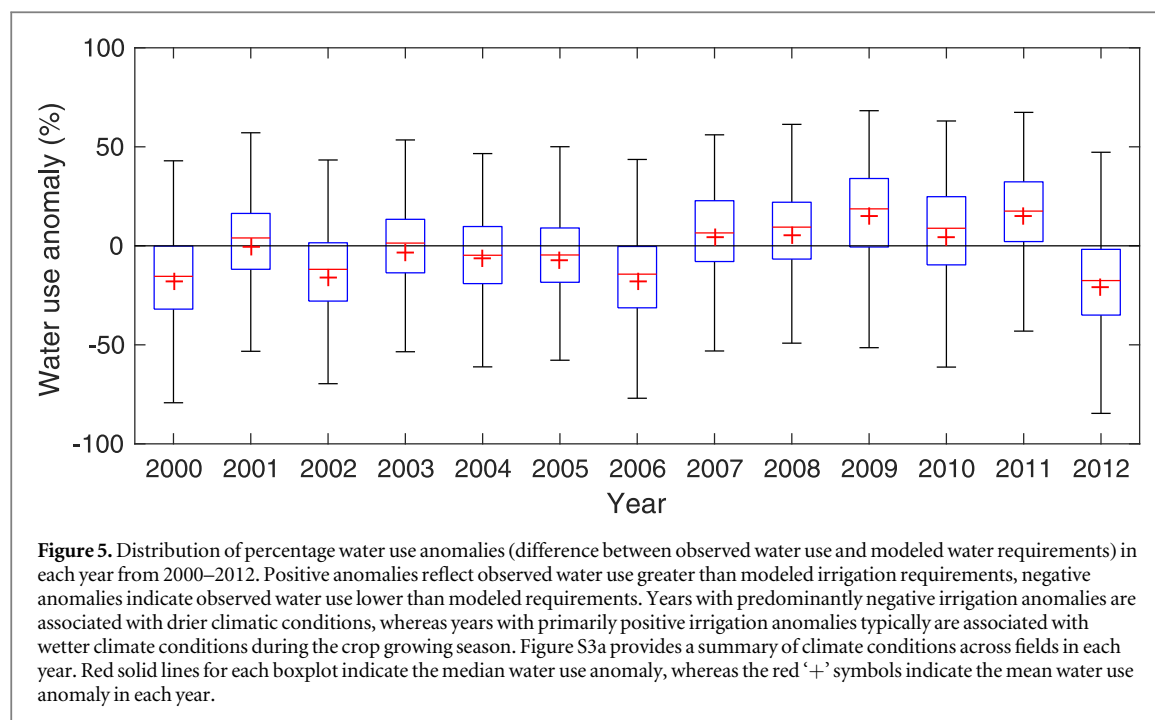
in our study region. However, it is important to highlight that there is also a consistent trend towards negative irrigation anomalies for wet versus dry years independent of soil type, indicating that soil properties may in fact magnify behavioral responses to interannual weather variability discussed previously.

A number of factors may explain the trends in irrigation anomalies observed in figures 4 and S9. Farmers in our study region whose fields have coarser soils are known to be enrolled disproportionately in interruptible energy supply contracts [32]. These contracts, which are common in rural areas of the United States, offer discounts on marginal energy prices of around 50%, and are used by rural electric providers to help to manage peak energy system loads. Fields with coarser soils are rarely enrolled in such interruptible contracts as sandier soils have limited storage capacity to buffer production against irrigation power outages. Marginal pumping costs on fields with coarser soils in our study region therefore are around double those of fields with finer soils [33], creating an economic driver for farmers to reduce irrigation water demand on fields with coarser soils [34, 35]. Additionally, water use allocations in our study region are also not differentiated by soil type. As a result, farmers whose fields have sandier soils will have greater incentives to adopt better irrigation management practices due to the higher gross irrigation demands on these fields. We argue that this response is likely to occur even if regulations are rarely physically binding, reflecting greater perceived concerns of farmers on sandier soils about exceeding allocations or depleting banked water reserves.

An alternative explanation for the results observed in figures 4 and S9 is that model estimates of irrigation requirements are biased systematically as a function of soil type. While it is impossible to discount conclusively the occurrence of systematic model bias, we suggest that such effects are unlikely as our soil water balance model has been shown to estimate accurately actual evapotranspiration and irrigation requirements for comparable corn hybrids and soil conditions in Nebraska [20, 36]. Our model is also based on the FAO-56 approach, which has been extensively tested for estimating crop water use in different settings worldwide [1] with no evidence of systematic bias reported in relation to soil type. Moreover, trends towards deficit irrigation, while greater in magnitude on sandier soils, are observed for all soil types in our study region, further suggesting that our results are not related principally to a systematic bias in model estimates.

3.3. Observed field-level irrigation water use varies more over space than modeled crop water requirements

In any given year, after considering the effects of weather and soil type on irrigation behavior, there is still large variability in observed irrigation water use



relative to crop irrigation requirements at field scales (figure 5). Across all years there are subsets of fields for which observed water use is as much as 50% or more both above and below estimated biophysical crop irrigation requirements. Previous studies have identified significant heterogeneity in crop yields at field scales in agricultural systems [37–39], and have also documented differences between observed water use and biophysical requirements at the district or regional scales [40–42]. However, to the best of our knowledge, our results are the first empirical evidence of such significant variability in the field-level irrigation behavior of individual farmers at a landscape scale.

We hypothesize that a number of interacting factors explain the large variability in irrigation behavior found in our study region. In particular, we demonstrate statistically that there are subsets of farmers whose water use rates are persistently above or below regional average, along with other groups of producers whose irrigation decisions fluctuate randomly from one year to another (figures S10 and S11). This finding indicates that important persistent and non-persistent differences in individual irrigator behavior exist superimposed on average responses to weather and soil characteristics, and is consistent with evidence from surveys of irrigation scheduling practices in neighboring regions of Nebraska [43]. Critically, heterogeneity in individual irrigation behavior could not be identified using either *in situ* or remote sensing based monitoring alone, highlighting how combining these data sources can generate new insights about field-level irrigation decision-making to support agricultural water management.

In addition to heterogeneity in farmers' individual irrigation behavior, differences between observed water use and modeled irrigation requirements may also reflect local-scale weather variability that is not captured accurately in model forcing datasets. Input weather data used to drive our water balance model is obtained from Daymet [26], a gridded dataset that has been developed and validated based on *in situ* weather station observations from across North America [44]. Recent studies have shown that Daymet reproduces accurately observed variability in temperature in the High Plains region, but, conversely, that some uncertainties exist in reported values of precipitation and reference evapotranspiration which are more strongly conditioned on localized weather patterns (e.g. convective rainfall, humidity) [45, 46]. While it is not possible to quantify explicitly the effects of weather input uncertainty on our results, we argue that such factors are unlikely to explain fully observed patterns and trends in irrigation water use anomalies. For example, significant negative irrigation anomalies observed in drought years would imply a systematic underestimation of rainfall and/or overestimation of reference evapotranspiration in these years by Daymet. Yet, this is inconsistent with evidence that spatial rainfall variability in our study region is low in drought years [46] and that Daymet tends towards under-prediction of reference evapotranspiration in drier years [45]. Similarly, it is also important to highlight that errors in modeled irrigation water requirements may also result from structural model uncertainties, for example due to the complexity of representing soil water dynamics and crop growth at field scales [20, 47]. However, we note that our model predictions of actual crop evapotranspiration and

irrigation demands have been validated successfully for corn hybrids grown in our study region under similar production conditions [20]. Consequently, while errors in model estimates of irrigation water requirements due to input data or model structure uncertainty cannot be discounted, we suggest that these are insufficient to explain the spatial and temporal patterns of irrigation anomalies observed in our analysis, which we argue instead are reflective of large producer-level variability in irrigation behavior that is consistent with recent surveys of irrigation practices in other areas of Nebraska [43].

4. Implications and conclusions

Comparing *in situ* water use observations and remotely sensed estimates of crop irrigation water requirements offers a valuable opportunity to understand how water is used across agricultural landscapes and, in doing so, support the management of limited freshwater resources. Using a dataset of over 9000 metered and remotely sensed irrigation records, our analysis shows that farmers' actual irrigation water use decisions diverge significantly from crop water requirements over both space and time. In particular, we demonstrate empirically that farmers on average have reduced irrigation water use relative to full crop requirements in drought years and on fields with low soil water holding capacity. In contrast, in wetter years and on fields with greater water holding capacity, we find that the majority of farmers irrigate in excess of estimated biophysical water requirements for optimal crop growth. Differences in water use behavior between wet and dry years have not resulted in systematic reductions in crop production in the region in drought years, indicating that these differences are likely to reflect adaptive shifts in farmers' irrigation management and scheduling decisions in order to minimize irrigation use in years of physical and/or economic water scarcity.

While previous studies have documented farmer adaptation to weather variability and water scarcity through shifts in crop choice or land management [48, 49], ours is the first to identify shifts at a landscape scale in field-level decision-making about applied irrigation water use. Our results demonstrate that opportunities may exist to incentivize reductions in groundwater pumping on some fields, in particular in wetter years where we observe that significant numbers of farmers irrigate in excess of estimated crop irrigation requirements. Reductions in groundwater pumping could be achieved through support for adoption of improved scheduling practices or technologies (e.g. soil moisture sensors), reducing energy costs of irrigation and increasing overall farm profitability. Improved irrigation management may also contribute to regional conservation of groundwater as a buffer against future drought [16, 50] and help to minimize

pumping impacts on freshwater ecosystems [51], although the magnitude of these benefits would depend on the hydrological effects of changes in irrigation patterns on return flows to the underlying aquifer [52]. Conversely, we also show that there are subsets of producers who may have already adapted irrigation management practices successfully to reduce water use in times of physical or economic scarcity without impacting crop yields significantly. Critically, where water supply is scarce or constrained, failure to consider these adaptive responses is likely to lead to an overestimation of the negative effects of drought and future climate change on crop production and rural economies in model-based agricultural impact assessments [53, 54].

In any given year, our findings further demonstrate that there is large variability in individual irrigation behavior, even after accounting for biophysical drivers of water use such as weather, soil type, crop choice, and irrigation technology. We attribute this variability to persistent and non-persistent differences in irrigation management practices between individual producers operating with equivalent irrigation technologies (i.e. center-pivots). This finding is consistent with surveys of irrigation practices close to our study region [43, 46], and highlights the need for greater collection and provision of fine-resolution *in situ* water use data, for example from real-time flow metering, to enable improved understanding about the fundamental behavioral, biophysical, and regulatory drivers of heterogeneous water use decisions over both space and time. Critically, such information would provide extremely valuable insights about variability in individual water use decision-making, which could be used to identify cost-effective management interventions to improve agricultural water use productivity at field-to-landscape scales.

Finally, our findings also provide important insights about the use of remote sensing to support field-level water use assessment and accounting. Remote sensing models can provide reliable predictions of irrigated areas [8–11] and consumptive crop water use [5–7]. However, our results indicate that it will be much harder for these methods to estimate accurately patterns of actual applied water use at field-levels due to the large unobserved spatial and temporal heterogeneities in farmers' individual irrigation behavior. As a result, we suggest that there will be significant uncertainty in model-based estimates of applied irrigation water use, in particular when applying fixed technology-based irrigation efficiency adjustments to remotely sensed estimates of consumptive water use [42, 55–58]. We suggest that efforts to monitor and enforce agricultural water rights based on remote sensing models therefore should focus on metrics of consumptive rather than applied water use. Critically, this may require large shifts in how water rights are managed in many regions worldwide,

highlighting the potential technical, legal, and regulatory challenges for use of remote sensing for monitoring of irrigation. To support these efforts, future research should seek to quantify spatial and temporal uncertainties in different model-based estimates of field-level applied water use, along with the resulting impacts on simulations of catchment water budgets and policy-relevant hydrological processes [4, 30, 59].

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