Water Resources Research

RESEARCH ARTICLE
10.1029/2020WR028378

Special Section:
The Quest for Sustainability of Heavily Stressed Aquifers at Regional to Global Scales

Key Points:
- Satellite remote sensing has been proposed as a low-cost solution to fill widespread gaps in monitoring of agricultural water use globally
- Validation of remote sensing models is limited with large uncertainties in estimates of irrigation water use at plot and regional scales
- Measurement errors create welfare losses for farmers and may constrain efforts to manage hydrologic impacts of irrigation abstractions

Supporting Information:
- Supporting Information S1

Correspondence to:
T. Foster,
timothy.foster@manchester.ac.uk

Citation:
Foster, T., Mieno, T., & Brozovic, N. (2020). Satellite-based monitoring of irrigation water use: Assessing measurement errors and their implications for agricultural water management policy. *Water Resources Research*, *56*, e2020WR028378. https://doi.org/10.1029/2020WR028378

Received 14 JUL 2020
Accepted 18 OCT 2020
Accepted article online 22 OCT 2020

©2020. The Authors.
This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

Satellite-Based Monitoring of Irrigation Water Use: Assessing Measurement Errors and Their Implications for Agricultural Water Management Policy

T. Foster[1], T. Mieno[2], and N. Brozović[2,3]

[1]Department of Mechanical, Aerospace and Civil Engineering, University of Manchester, Manchester, UK, [2]Department of Agricultural Economics, University of Nebraska-Lincoln, Lincoln, NE, USA, [3]Robert B. Daugherty Water for Food Global Institute, University of Nebraska-Lincoln, Lincoln, NE, USA

Abstract Reliable accounting of agricultural water use is critical for sustainable water management. However, the majority of agricultural water use is not monitored, with limited metering of irrigation despite increasing pressure on both groundwater and surface water resources in many agricultural regions worldwide. Satellite remote sensing has been proposed as a low-cost and scalable solution to fill widespread gaps in monitoring of irrigation water use in both developed and developing countries, bypassing the technical, socioeconomic, and political challenges that to date have constrained in situ metering. In this paper, we show through a systematic meta-analysis that the relative accuracy of different satellite-based irrigation water use monitoring approaches remains poorly understood, with evidence of large uncertainties when water use estimates are validated against in situ irrigation data at both field and regional scales. Subsequently, we demonstrate that water use measurement errors result in large economic welfare losses for farmers and may negatively impact ability of policies to limit acute and nonlinear externalities of irrigation abstraction on both the environment and other water users. Our findings highlight that water resource planners must consider the trade-offs between accuracy and costs associated with different water use accounting approaches. Remote sensing has an important role to play in supporting improved agricultural water accounting—both independently and in combination with in situ monitoring. However, greater transparency and evidence is needed about underlying uncertainties in satellite-based models, along with how these measurement errors affect the performance of associated policies to manage different short- and long-term externalities of irrigation water use.

1. Introduction

Agriculture is the main sectoral user of freshwater worldwide. As competition over limited water resources increases, policymakers in many regions are seeking to limit agricultural water withdrawals and incentivize improvements in the productivity of irrigation water use. The types of policies and interventions that have been proposed or implemented vary between regions, ranging from volumetric pumping quotas or power rationing (Aarnoudse et al., 2019; Foster et al., 2017; Sidhu et al., 2020), taxes on extraction or reforms to water pricing (Fishman et al., 2016; Rad et al., 2020; Smith et al., 2017), to water markets (Calatrava & Martínez-Granados, 2019; Palazzo & Brozović, 2014; Rouillard, 2020). However, a key requirement in each case is the ability to monitor farmers' water withdrawals in order to enforce rules governing individual abstraction rates (OECD, 2015) and determine future sustainable abstraction limits (Butler Jr et al., 2018).

Despite the importance of monitoring for water management, the overwhelming majority of agricultural water use worldwide—both from groundwater and surface water—remains unmetered (OECD, 2015). For example, a recent report by the Murray-Darling Basin Commission in Australia highlighted that around 30% of the total surface water abstractions were unmetered (MDMA, 2017), with monitoring gaps of up to 75% in some parts of the basin (Grafton, 2019; Hanemann & Young, 2020). Similarly, estimates from the U.S. Department of Agriculture (USDA, 2019) show only 36% of groundwater irrigation wells in the United States are equipped with flow meters (Figure 1), with large monitoring gaps in states such as California and Texas that have experienced severe aquifer depletion over recent decades (Scanlon et al., 2012). In low-income countries, gaps in agricultural water use accounting are even more pronounced, with almost nonexistence

10.1029/2020WR028378

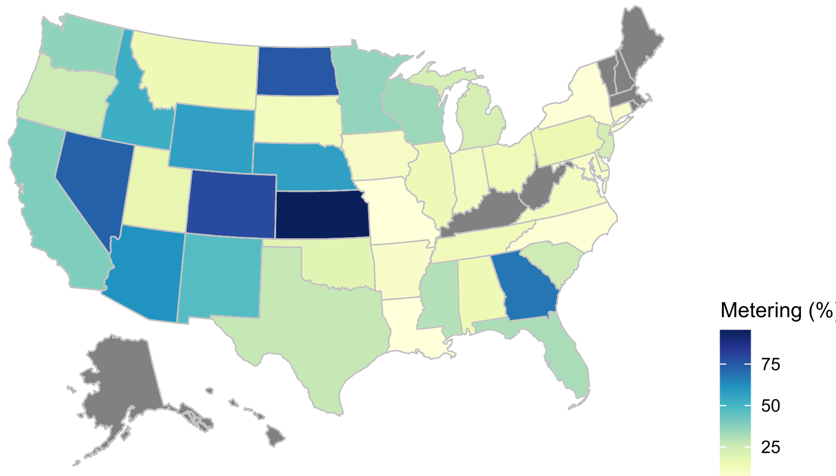

Figure 1. Percentage of groundwater irrigation wells with an attached flow metering device for each state in the United States. States shaded in gray, for which data are not plotted, contain less than 1,000 active groundwater irrigation wells. Data are obtained from the U.S. Department of Agriculture's 2018 Irrigation and Water Management Survey (USDA, 2019) and includes flow meters installed for both regulatory and nonregulatory purposes.

monitoring and reporting of agricultural water use in areas of intensive irrigation across Africa, Asia, and the Middle East (Balasubramanya & Stifel, 2020)

A key factor underpinning the low levels of metering of water abstractions for irrigation is the difficulty faced by managers and regulators in maintaining reliable and complete records of the locations of abstraction wells or diversions. In surface water irrigation systems illegal off-takes from canals or rivers are common (e.g., Hanemann & Young, 2020), in particular in developing countries where diversions may be small scale and based on simple temporary infrastructure that exist outside of official planning and permitting processes (Veldwisch et al., 2019; Woodhouse et al., 2017). Monitoring locations of groundwater irrigation is often even more challenging because the infrastructure (pumps and wells) used to abstract water is commonly entirely privately owned and operated by farmers (Al Naber & Molle, 2017; De Stefano & Lopez-Gunn, 2012; Shah, 2014; Wester et al., 2009). Illegal or unregistered irrigation wells exist in developed countries where permitting and monitoring on paper are mandated by governments (De Stefano & Lopez-Gunn, 2012) and are widespread in low-income countries where most farmers are small scale and reliant on wells drilled without official permission or licensing (Al Naber & Molle, 2017; Shah, 2014; Wester et al., 2009).

Where locations of irrigation abstractions are known, implementing and enforcing in situ metering remains challenging for a number of reasons. Farmers may oppose or lobby against the installation of meters due to concerns about increased future regulation (López-Gunn, 2012; Rinaudo et al., 2016). When meters are installed, collecting readings and maintaining monitoring infrastructure can be extremely costly and time-consuming for resource-limited regulators (Closas & Molle, 2018; Hoogesteger, 2018; Novo et al., 2015) and must be accompanied by strong sanctions and penalties to deter rule breaking or cheating (Montginoul et al., 2016). For example, the Upper Republican Natural Resources District in Nebraska in the United States has in recent years revoked groundwater rights to irrigators who have been caught attempting to bypass flow meters (Brozović & Young, 2014). These types of responses, however, are typically the exception to the rule. Instead, in many regions, metering systems are never installed or quickly fall into disrepair due to meter tampering, poor maintenance, and insufficient penalties for rule breaking (Molle & Closas, 2020b).

Motivated by the technical, economic, and political challenges associated with in situ metering, researchers and water managers are seeking alternative solutions for monitoring distributed agricultural water use to support regulation, planning, and management. One such approach is through use of satellite remote sensing. Remote sensing has been widely used to monitor irrigated areas over space and time (Ambika et al., 2016; Deines et al., 2019; Vogels et al., 2019). However, more recently, there has been growing interest among researchers and policymakers in the potential to use satellite-based remote sensing as a tool for monitoring irrigation rates in the absence of, or as a substitute for, in situ metering (Brocca et al., 2018; Hunink et al., 2015). Satellite data are seen as a key tool for future water use monitoring and governance in a number of regions, including as part of California's Sustainable Groundwater Management Act (SGMA) in the United States (Babbitt et al., 2018) and Murray-Darling Basin Plan (MDBP) in Australia (Bretreger et al., 2019). Similarly, water accounting based on open-access remote sensing data has been proposed as a solution for spatially explicit monitoring of agricultural water use, in particular in smallholder farming systems with negligible in situ water use monitoring infrastructure. For example, the U.N. Food and Agriculture Organization, UNESCO-IHE, and partners have widely championed the Water Accounting Framework (Karimi et al., 2013; Molden & Sakthivadivel, 1999) to support agricultural water management, while the World Bank through its Global Water and Sanitation Partnership has emphasized the important role of satellite monitoring of evapotranspiration (ET) and irrigation water use in supporting future water resource planning and decision-making (Capdevila & Herrmann, 2019).

Despite this, at present there remains significant uncertainty about the accuracy and reliability of satellite-based approaches for monitoring irrigation water use in particular at the scales relevant for monitoring and enforcement of agricultural water management policies. Errors in satellite-based monitoring and accounting of irrigation water use have potential to generate significant negative impacts on farmers (e.g., if their water use is overestimated leading to unfair restrictions or penalties) and water resource sustainability (e.g., if agricultural water users are incorrectly allowed to exceed intended abstraction limits). In this study, we address these knowledge gaps through a comprehensive analysis of the uncertainties and associated welfare implications of satellite-based monitoring of irrigation water use. We first conduct a meta-analysis of existing published research to examine the scale and underlying causes of measurement errors resulting from satellite-based water use monitoring. We show that studies using satellite data for irrigation water use estimation commonly lack adequate validation against in situ data and report significant uncertainties when used to monitor water use at plot scales. Subsequently, we demonstrate theoretically that these errors in water use measurement will induce welfare losses for farmers and have the potential to negatively affect the performance of water management policies where irrigation abstraction has nonlinear impacts on other water users and the environment. Our findings show that there are a number of technical and institutional challenges for use of remote sensing for water use monitoring and accounting and highlight the need for greater research focus on validation and assessment of trade-offs between monitoring accuracy and costs to support effective and judicious use of satellite data in agricultural water management and policy.

2. Uncertainty in Satellite-Based Water Use Estimates

2.1. Study Selection and Synthesis

In order to assess the status of research concerning satellite-based monitoring of irrigation water use, including associated levels and sources of measurement uncertainty, we first conducted a systematic review of the peer-reviewed literature by searching Scopus for research articles published since 1980 and containing a selection of relevant keywords. Specific keywords considered were combinations "irrigation" and one or more of "withdrawal" or "estimate" or "use" or "requirement" and one or more of "satellite" or "remote sensing" or "Earth observation."

Of the 2,126 papers initially identified, a total of 73 was selected for full review following assessment of information given abstracts and methodologies of the papers of which 41 were retained within the final sample for our systematic review (see Table S1 in the supporting information for a full list of these 41 studies). The sift of papers focused attention on studies that used Earth observation data to estimate irrigation application rates or requirements—comparable to what would be provided by in situ flow meters—excluding studies that sought to use remote sensing to quantify total crop ET fluxes (i.e., consumptive water use) or irrigated areas.

Each of the 41 papers retained was read and reviewed in full, recording a number of key details about each study. Specifically, we sought to document and record information about the (i) geographic and temporal focus of the analysis, (ii) formulation—for example, applied irrigation versus irrigation requirements—in which irrigation use was estimated, (iii) types of satellite products and models used in the analysis, and (iv) spatial and temporal resolution of irrigation water use estimation.

Alongside information about the key characteristics of each study and the methodological approach used to estimate irrigation water use, we also sought to record and synthesize evidence about the validation of satellite-based water use estimates. We collected information for each study about any in situ monitoring data used to assess accuracy of satellite-based water use estimates, including the source, characteristics, and

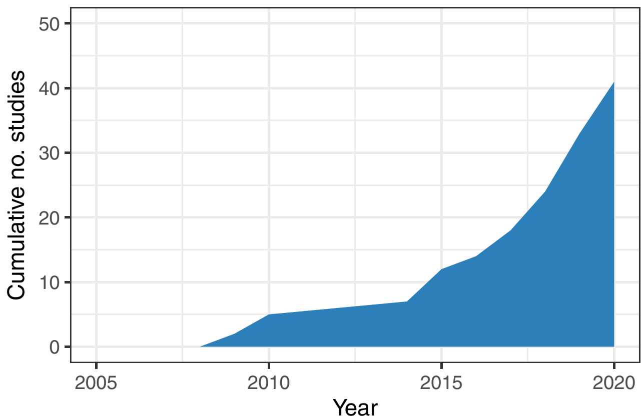

Figure 2. Cumulative total number of peer-reviewed studies since 2005 that use remote sensing to estimate irrigation water use or requirements identified through our systematic literature review as described in section 2

spatial and temporal resolution of this ground-truth data. Accuracy of water use estimates was recorded where this information was reported, along with information about the specific performance metrics and scales (spatial and temporal) used when producing these metrics.

Where validation was performed and reported in a study, information was also recorded about any key factors highlighted by authors as determinants of higher or lower levels of accuracy in satellite-based water use estimates. We collated evidence about the key factors constraining accuracy of satellite-based assessments of irrigation water use to inform subsequent discussions about future needs, challenges, and opportunities to enable uptake of such methods in policy and practice.

2.2. Study Characteristics and Estimation Approaches

Our review highlights that use of satellite remote sensing for estimating rates of irrigation water use is an emerging and rapidly developing literature. Figure 2 shows that 85% ($n = 35/41$) of papers were published from 2015 onward, with none of the identified studies published prior to 2009. These trends are consistent with the greater availability and accessibility of satellite data over recent years, along with increasing resolution and spectral detail of remote sensing products and imagery needed to support spatially and temporally explicit irrigation water use estimation.

Just under half of studies ($n = 20/41$) explicitly sought to estimate irrigation water use or requirements at individual field or farm scales, typically using data from satellites providing imagery at high spatial resolution such as Landsat satellites, Sentinel-2, or SPOT (Satellite Pour l-Observation de la Terre). The remaining studies estimated irrigation water use on a gridded basis (0.25–32.5 km) matching the resolution of underlying satellite imagery, with estimates sometimes aggregated to the level of an irrigation scheme or catchment for subsequent reporting and analysis. Critically, in many cases the spatial resolution of gridded irrigation water use estimation was often significantly coarser than the typical plot or field sizes in the study region. For example, Cheema et al. (2014) estimate groundwater irrigation withdrawals on a 1 km^2 grid that far exceeds typical smallholder plot sizes in their study area—the Indus Basin in Pakistan. Similar characteristics were also observed for the temporal scale and length of studies. Irrigation water use was quantified over a median 3 years or seasons (range from 1 to 21 years or seasons), with 17/41 studies conducting analysis for only a single season or year.

Three main methodological approaches to the estimation of irrigation water use emerge from our meta-synthesis that reflect the primary type of satellite data used to derive estimates of irrigation water use. First, 20 out of 41 studies use remotely sensed thermal infrared imagery (e.g., from MODIS—Moderate Resolution Imaging Spectroradiometer—or Landsat) to estimate crop ET rates, which are then converted in to estimates of consumptive irrigation water use by subtracting an estimate of effective rainfall. Variations on this approach involve calculating the difference between estimated ET fluxes for irrigated locations with those for neighboring rainfed pixels (Romaguera et al., 2014; Van Eekelen et al., 2015; Vogels et al., 2020) or, alternatively, with ET fluxes simulated by land surface hydrology models. The latter typically do not include representations of irrigation practices, meaning that the additional ET "observed" in reality through satellite remote sensing can be attributed to irrigation water consumption (Anderson et al., 2015; Droogers et al., 2010; Lopez Valencia et al., 2020). In a subset of studies ($n = 11/20$), estimates of consumptive irrigation water use are converted to applied or abstracted water by applying efficiency adjustment factors to account for nonconsumptive losses such as deep percolation or runoff. Typically, these factors are conditioned on the types of irrigation technology used by farmers in the region and do not vary between farmers operating the same technology or over time. For example, Msigwa et al. (2019) and Van Eekelen et al. (2015) both assume a constant irrigation application efficiency of 75% for case studies in southern Africa based on assumptions about prevailing irrigation technology mixes across their study areas.

A second category of models estimate irrigation water use based on satellite soil moisture observations from either passive (e.g., SMOS—Soil Moisture Ocean Salinity and AMSR—Advanced Microwave Scanning

Radiometer) or active (e.g., ASCAT—Advanced SCATterometer and Sentinel-1) microwave sensors. Similarly to thermal-infrared models, two broad methodological approaches are applied in soil moisture-based models of irrigation water use. First, "observed" soil moisture changes can be used in conjunction with meteorological data and soil moisture balance models to solve for the unknown rate of irrigation (Brocca et al., 2018; Jalilvand et al., 2019). ET fluxes used in the inversion of soil water balance models are typically estimated using empirical relationships between ET and soil moisture. However, some studies also utilize satellite-based ET time series, combining information from thermal-infrared and microwave sensors. An alternative approach for isolating effects of irrigation is to compare observed soil moisture changes detected using microwave sensors with soil moisture changes predicted for the same location by land surface models that omit irrigation processes (Zaussinger et al., 2019; Zohaib & Choi, 2020). A variation on this approach is adopted by Abolafia-Rosenzweig et al. (2019) who assimilate satellite soil moisture data within a land surface hydrological model Variable Infiltration Capacity model (VIC) to derive estimates of the underlying rate of irrigation water use. As for thermal-infrared models, additional adjustment factors based on technical system efficiencies may subsequently be applied to determine applied or abstracted rates of water, in particular to account for nonconsumptive losses of irrigation water before entering the soil profile (e.g., surface runoff and canopy evaporation) that are not captured by satellite soil moisture data.

Finally, the third category of models used to estimate irrigation water use are crop coefficient models. These models utilize reflectance-based estimates of crop coefficients, which capture crop vegetation condition on a given day obtained as a function of vegetation indices (e.g., normalized difference vegetation index [NDVI] and enhanced vegetation index [EVI]) derived from different combinations of spectral bands captured by satellite imagery (Campos et al., 2017). Crop coefficients are then inputted, along with meteorological data, to soil water balance models to estimate rates of irrigation given assumptions about the level of soil moisture depletion at which irrigation will be triggered and expected application and conveyance efficiencies of water use. A key difference between crop coefficient and thermal-infrared or soil moisture-based models is that reflectance-based crop coefficient models are most commonly used to provide estimates of crop irrigation requirements rather than actual abstraction rates (Abuzar et al., 2017; Campos et al., 2017; Foster et al., 2019; Gonçalves et al., 2020; Santos et al., 2010; Segovia-Cardozo et al., 2019; Vuolo et al., 2015). This is because reflectance-based crop coefficients capture reductions in crop ET caused by suboptimal crop development over the growing season but do not provide direct information about additional reductions in crop ET as a result of water stress limiting plant transpiration. Instead, underlying soil water balance models typically assume that farmers' trigger irrigation when soil moisture depletion reaches the level at which stomatal closure would be triggered (Foster et al., 2019; Gonçalves et al., 2020), thus generating an estimate of the amount of irrigation that would need to have been applied to avoid water stress. Where these assumptions are violated, or if uncertainties exist in the assumed threshold for initiation of stomatal closure or other model inputs (e.g., irrigation application efficiencies), then estimates of irrigation water use are likely to diverge from true abstraction rates (Peña-Arancibia et al., 2016).

2.3. Model Validation and Uncertainties

Satellite remote sensing provides an indirect measure of irrigation water use, and therefore, it is important to verify the accuracy of water use estimates against ground-truth data. Of the 26 studies that estimate irrigation water use (i.e., excluding those studies focused solely on estimating crop irrigation requirements), we find that only 7 compare estimates of irrigation water use against real-world in situ observations at field or farm scales (Figure 3) that are the primary unit of management for agricultural water use in most regions. Of these seven studies, six compared estimates of irrigation water use with in situ records for less than 50 unique fields or farms with only one study (Bretreger et al., 2019) utilizing a more substantial ($n = 1{,}365$) ground-truth data set. Of the other 19 studies, Figure 3 shows that 11 studies conduct no validation or rely solely on synthetic water use data (i.e., estimates of water use derived using models considering idealized farmers behavior). The remaining (eight studies) compare estimates against water use statistics aggregated at administrative levels, for example, an irrigation district, county, state, or nation.

Similar patterns are also observed when considering the number of years of in situ data used for validation, which ranges from 1–17 years (median of 4 years) for studies that performed some comparison with observation data. Validation of satellite-derived estimates is commonly only conducted for a limited range of hydrometeorological conditions, which may limit insights about model performance given that irrigation efficiency (Foster et al., 2019) and meteorological data uncertainties (Gibson et al., 2017; Mourtzinis

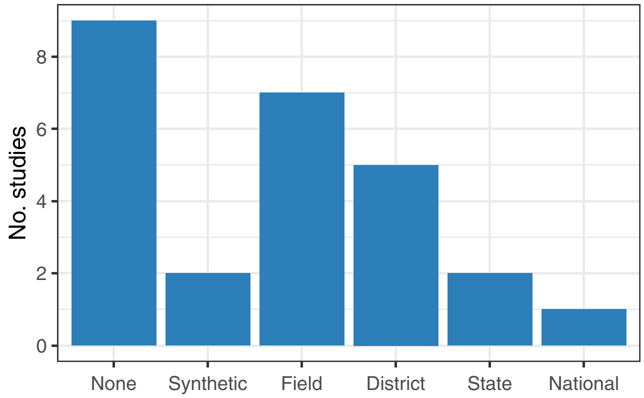

Figure 3. Spatial scale at which each of the 26 studies estimating irrigation water use based on satellite remote sensing reviewed were validated. "None" denotes studies for which no validation was conducted, and "Synthetic" refers to studies that were tested against simulated water use data

et al., 2017) have been shown to be strongly dependent on hydroclimatic conditions. Studies by Brocca et al. (2018) and Abolafia-Rosenzweig et al. (2019) provide notable exceptions to the short temporal length of most validation exercises. These studies instead leveraging differences in rainfall patterns between sites in different agroclimatic regions to conduct more detailed testing of the performance of soil moisture-based irrigation water use estimation algorithms. However, these comparisons are based on synthetic water use data and, as a result, are limited in their ability provide robust conclusions about the reliability of satellite water use estimation in real-world agricultural systems.

Direct comparison of reported accuracies of satellite-based irrigation water use estimates is challenging due to differences in reported performance metrics, lack of access to underlying data and model outputs, along with large variability in the scales (spatial and temporal) and sources of validation data used in each study. However, from the limited set of studies that conduct multiplot validation at field or farm scales, it is clear that large differences exist between actual and estimated irrigation use rates at field or farm scales. Bretreger et al. (2019) find that errors in water use estimates range between ±20% and 60% even when averaged over multiple plots and years, with significantly larger errors for individual plots or when varying assumption about crop types, management practices, and baseline meteorological data. Similar errors are also reported in other field or farm-scale assessments. Garrido-Rubio et al. (2020) report plot-level root-mean-square error (RMSE) in irrigation water use by crop type ranging from 44–176 mm (6–77% of actual water use), while Battude et al. (2017) report RMSE's of 32–60 mm (19–35% of actual water use) at field levels even when averaging estimates over several years. Lower, but still significant, errors (RMSE of 44 mm relative to actual mean water use of 245 mm) are reported by Olivera-Guerra et al. (2020) for five plots over two to four seasons using a thermal-infrared-based model. Olivera-Guerra et al. (2020) focus on wheat production in Morocco where precipitation and cloud cover are minimal and use validation data from experimental plots, showing that uncertainty in water use estimation remains significant even if it is possible to reduce errors introduced by input data uncertainty or unobserved heterogeneity in farmer irrigation management practices.

Deviations between estimated and observed water use are still found when comparing estimated and observed water use at larger spatial scales (e.g., irrigation district or administrative region), suggesting that aggregation of water use estimation in most cases does not smooth out of errors introduced by localized variations in farmer irrigation behavior or input data uncertainty. Peña-Arancibia et al. (2016) find that estimated annual district-scale irrigation extractions based on thermal-infrared ET models contain errors of around 20–100%, with larger errors observed for groundwater compared to surface water extractions. Similarly, large errors are also observed for studies using satellite soil moisture models. Jalilvand et al. (2019) obtain aggregated errors of 13 mm/month for an irrigated region in Iran, while Zaussinger et al. (2019) report errors in state-level water use estimation in the United States of 5.2–5.3 km^3/yr. One exception is Hunink et al. (2015) who report smaller RMSE's—7% to 13% for scheme-level water use estimates aggregated across plots with similar crop types—in a study in SE Spain using NDVI-based crop coefficients. Largest errors are reported for normal rainfall years relative to drought years, suggesting a potential influence of weather conditions on estimation accuracy due to the confounding effect of precipitation uncertainty on satellite-based irrigation estimates.

Overall, we find that only those studies that utilize stylized error-free synthetic data for validation generally report closest correspondence with water use validation data. Studies by Brocca et al. (2018) and Abolafia-Rosenzweig et al. (2019), for example, report correlation coefficients for soil moisture-based irrigation estimates of greater than 0.9 in some scenarios. These results reflect the fact that synthetic model experiments assume that all input data to algorithms used to estimate irrigation water use, including meteorological data, satellite imagery, and representations of farmer irrigation behavior, are available and can be defined without error or uncertainty. When these assumptions are relaxed, accuracy of water use estimation is shown to deteriorate, with significant reductions in the accuracy of irrigation estimation using satellite soil moisture data as either the return time or noise of satellite soil moisture observations is artificially increased to levels that are consistent with real-world Earth observation data (Brocca et al., 2018; Abolafia-Rosenzweig et al., 2019).

2.4. Sources of Measurement Error and Uncertainty

Drawing on evidence reported in the 41 studies captured in our synthesis of existing published literature, along with wider supporting literature on satellite ET estimation, three main factors underpinning reported uncertainty in satellite-based irrigation water use estimation can be identified: (1) accuracy and resolution of satellite data sets, in particular relative to the scales of in situ data and farmer irrigation decision-making; (2) quality of input meteorological data used in estimation of irrigation water use; and (3) uncertainty in the specification of farmer irrigation behavior heuristics and management practices, including the scheduling and efficiency of irrigation decisions. Each of these is discussed in turn below.

2.4.1. Satellite Data Uncertainty and Resolution

Remote sensing models of irrigation water use are based on indirect estimates of ET, soil moisture, and/or crop condition obtained from multispectral or microwave satellite imagery. Measurement of these variables contains uncertainties—due to noise or errors in raw imagery, along with uncertainty in the underlying algorithms used to translate raw spectral signals—that, in turn, will propagate in to estimates of irrigation water use. Accuracy of actual ET estimation or crop coefficients from multispectral satellite imagery, for example, has been shown to be reduced due to limited spatial resolution of satellite data products relative to agricultural field sizes (Fisher et al., 2017; Vogels et al., 2019), gaps in the frequency of image acquisition caused by cloud cover (Senay et al., 2016), uncertainties in the measurement via satellites of key inputs to energy balance models such as surface temperatures or net radiation (Fisher et al., 2008), difficulties in adequately parametrizing effects of soil moisture (Purdy et al., 2018), or advection processes (Aragon et al., 2018) on ET fluxes, along with operator errors or biases introduced when implementing ET estimation algorithms (e.g., in the selection of hot/cold pixels when constraining surface energy balance models— Long & Singh, 2013). Moreover, for a given location and time, large differences often are found in the absolute values of actual ET estimated using different energy balance algorithms and models (Biggs et al., 2016; Ershadi et al., 2014; Gonzalez-Dugo et al., 2009; Javadian et al., 2019; Medellin-Azuara et al., 2019), with little consensus in the scientific literature about the best-performing model types (Zhang et al., 2016). Together with limited availability of in situ ET observation data for validating satellite estimates, this creates challenges for water managers considering use of remotely sensed ET data in irrigation water use estimation and monitoring.

Similar difficulties for quantifying and validating uncertainties are also observed when using satellite-based soil moisture products for irrigation use estimation. ET flux estimates are a key input to soil moisture balance algorithms (Brocca et al., 2018), and, as a result, uncertainties in estimates of these fluxes—whether estimated using satellite data or derived from empirical relationships with soil moisture condition—will influence accuracy of resulting irrigation water use estimation. Noise in the observed soil moisture signal will also bias soil moisture change retrievals and exacerbate uncertainty in irrigation water use estimation based on these data. Data noise and resulting detection of spurious irrigation signals have been attributed to the confounding influence of vegetation backscatter on soil moisture signals along with the coarse resolution of satellite soil moisture products (Abolafia-Rosenzweig et al., 2019; Brocca et al., 2018; Kumar et al., 2015; Zaussinger et al., 2019). Existing soil moisture products have a spatial resolution (25–50 km) that far exceeds that of individual plots in developed-world agricultural systems (Zaussinger et al., 2019) and are orders of magnitude larger than typical smallholder plots (Vogels et al., 2019). Local (i.e., subpixel) effects of irrigation will be blurred out in landscapes with complex heterogeneity in agricultural land use, irrigation management practices, or topography, although aggregated irrigation signals may be detectable where the majority of land within a pixel is irrigated and cropping/management practices are mostly homogeneous (Lawston et al., 2017). As a result, coarse-scale soil moisture products currently are unlikely to be able to accurately detect local patterns of irrigation at field or farm scales that are critical for spatially explicit water use accounting, management and policy enforcement.

2.4.2. Meteorological Data Quality

Estimates of irrigation water use based on satellite remote sensing are affected by uncertainty not only in satellite-derived variables but also in other inputs to irrigation water use models. In particular, meteorological data are a key input to model-based estimates of irrigation water use and an important driver of actual farmer irrigation decision-making. However, meteorological data in many regions are subject to significant uncertainties at scales (field to district) relevant for water management and regulation.

Precipitation gauging networks in many parts of the world—especially in developing countries—are declining and often sparsely distributed (Menne et al., 2012). The limited observation data that do exist also may suffer from large data gaps and errors, exacerbated by the fact that not all countries make precipitation data from national monitoring networks freely available. As a result, the only spatially and temporally consistent precipitation data sets available in many locations are from satellite or model reanalyses data sets (e.g., Funk et al., 2015). As with ET flux estimates, absolute values from different gridded precipitation products can differ substantially from each other (Beck et al., 2020). Large uncertainties exist in the accuracy of satellite precipitation data sets in regions where in situ data is unavailable to support calibration and validation, posing substantial challenges for model-based solutions for irrigation water use accounting and agricultural climate risk assessment in these regions (Parkes et al., 2019; Van Wart et al., 2013). Critically, in the absence of detailed in situ observations it is extremely difficult to evaluate or compare the relative performance of alternative gridded precipitation products, thus limiting capacity of users to quantify or minimize uncertainty in subsequent irrigation water use estimates based on these data.

While the density and completeness of in situ precipitation records in North America and Europe are much higher (Menne et al., 2012), significant levels of uncertainty can still exist in the estimation of precipitation at field levels as part of water use estimation for groundwater policy or water rights enforcement. Precipitation event timing and rates can vary between rain gauges, in particular in regions characterized by local convective rainfall regimes. For example, Gibson et al. (2017) note large differences in rainfall cumulation and seasonal totals between several closely spaced (<10 km) gauges in southwestern Nebraska in the United States. Gridded weather data sets in regions with extensive monitoring networks for calibration and validation also still display meaningful errors in local precipitation estimates. Mourtzinis et al. (2017) find significant differences between estimates of seasonal water deficits and crop yields based on in situ weather stations and high-resolution gridded weather data sets (Daymet and PRISM) in Midwest of the United States. These trends are broadly consistent with reported uncertainties in irrigation water use estimates from studies in our sample based on satellite soil moisture, which typically higher levels of estimated accuracy in semiarid and arid environments (Brocca et al., 2018) or drought years (Hunink et al., 2015) where precipitation contributes a small or negligible amount of crop water use. This reflects the fact that soil moisture models derive estimate of irrigation water use (e.g., Abolafia-Rosenzweig et al., 2019; Brocca et al., 2018; Jalilvand et al., 2019) as a function of the difference between the total water that is "observed" to enter the soil (i.e., from a change in soil moisture condition) minus inflows from precipitation. Where irrigation and precipitation occur simultaneously, uncertainty in precipitation may therefore mask or bias the irrigation signal in the soil moisture time series in ways that would be less likely to occur if precipitation was low or minimal during the growing season.

While precipitation data are cited as key driver of uncertainty in estimated irrigation water use, it is also important to note that other meteorological input variables may influence accuracy of water use estimation. Bretreger et al. (2019) show that uncertainty in the estimation of reference ET, which is influenced by factors such as temperature, humidity, and wind speed, can also lead to large variations in resulting estimates of irrigation water use. Likewise, as previously noted, estimates of crop ET based on thermal-infrared satellite imagery are affected by uncertainty in meteorological data such as surface air temperature and vapor pressures (Fisher et al., 2017). Together, uncertainties in key water fluxes (i.e., precipitation and ET) have potential to generate significant errors in estimates of irrigation water use, which will not be addressed solely by improving spatial or temporal resolution of satellite imagery.

2.4.3. Heterogeneity in Irrigation Behavior and Efficiency

Irrigation abstraction rights, where defined, typically are specified and enforced in terms of a quantity of abstracted or applied water use (Molle & Closas, 2020a). To support monitoring and management, it is critical that remote sensing models are able to estimate accurately the total amount of water abstracted by a farmer as opposed to only the consumptive rate of irrigation water use that does not consider inefficiencies associated with irrigation application or conveyance. As discussed in section 2.2, this is typically achieved by application adjustment factors to convert estimates of consumptive irrigation water use in to estimates of applied or abstracted rates of irrigation (e.g., Cheema et al., 2014; Fehri et al., 2019; Msigwa et al., 2019; Van Eekelen et al., 2015; Vogels et al., 2020).

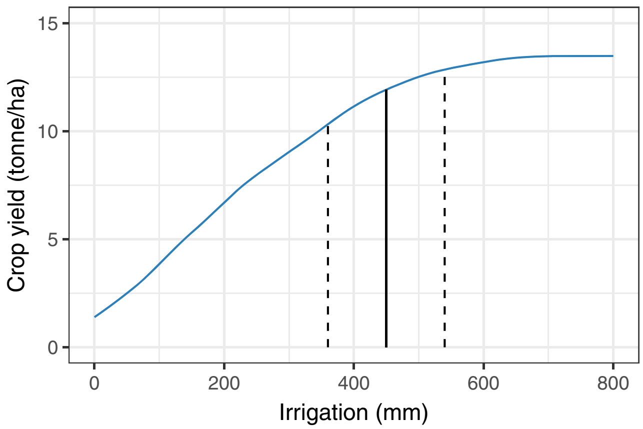

Figure 4. Crop-water production showing the relationship between applied irrigation and crop yield for maize in the southern High Plains region of the United States drawn from data presented in Foster and Brozović (2018). The black vertical solid line illustrates a hypothetical water use constraint of 450 mm (approximately 18 in.), with the black vertical dashed lines showing hypothetical permutations of this allocation with measurement errors of ±20%.

In practice, these assumptions are unlikely to capture the true heterogeneity in field or farmer level irrigation efficiency. Several studies in our sample estimate crop irrigation requirements using either thermal-infrared or crop coefficient models and compare these estimates to in situ abstraction data (Abuzar et al., 2017; Campos et al., 2017; Elnmer et al., 2018; Foster et al., 2019; Gonçalves et al., 2020; Ma et al., 2018; Santos et al., 2010; Segovia-Cardozo et al., 2019; Vuolo et al., 2015; Wu et al., 2015). Universally, these studies show that efficiency—defined here as the ratio of irrigation abstracted or applied to crop irrigation requirements—varies significantly both between fields and over time. For example, Foster et al. (2019) analyze over 9,000 irrigation records in Nebraska showing that farmers increase irrigation efficiency in drought years and on finer textured soil types, largely in response to higher costs of irrigation pumping. Similar results are also reported by Segovia-Cardozo et al. (2019) and Gonçalves et al. (2020) for case studies in Spain and United States, respectively, who both identify large farmer-level heterogeneity in irrigation efficiency that is not captured by heterogeneity in technology choice, while Van Eekelen et al. (2015) also note that true irrigation efficiencies are likely to vary significantly from their baseline assumption of 75% across Incomati basin in southern Africa.

Given these findings, we argue that while a fixed technological efficiency may be able to predict reasonably water use average over multiple years and fields, such assumptions are likely to mask important spatial and temporal heterogeneity in irrigation water application or abstraction rates at plot scales. Indeed, studies in our sample show that accuracy of water use estimates in general improves when estimates are averaged over a large number of plots and years (Foster et al., 2019), suggesting that, in some cases, errors in satellite-based estimates may cancel out at larger spatial and temporal scales. However, as highlighted in section 2.3, notable errors can still exist even after such averaging is conducted. Importantly for efforts to utilize remote sensing as a low-cost substitute for in situ monitoring, local-scale uncertainties will persist irrespective of the accuracy of ET or meteorological data sets, highlighting the importance of improvements in behavioral as well as biophysical data to support irrigation water use estimation.

3. Economic and Hydrologic Impacts of Measurement Errors

One of the proposed uses of satellite-based water use estimates is to support field-level water use accounting and water rights management (Droogers et al., 2010), addressing challenges to monitoring and enforcement of water use allocations posed by limited in situ metering of irrigation wells. Given observed uncertainty in satellite-based water use estimates at these resolutions (section 2.3), it is important to assess what implications measurement errors might have for both farmers' economic returns and the effectiveness of water management policies.

To examine the welfare implications of water use measurement errors for farmers, Figure 4 presents a production function that illustrates relationship between irrigation inputs and crop yield outputs. The production function given in Figure 4 is drawn from an example presented in Foster and Brozović (2018) for maize production in the High Plains region of the central United States. This production illustrates the nonlinear relationship between applied irrigation and crop yields, which is not specific to our case study crop or region. Indeed, a range of studies have shown that crop yields typically exhibit an s-shaped or curvilinear relationship with crop yields (English et al., 2002; Fereres & Soriano, 2007; García-Vila & Fereres, 2012; Geerts & Raes, 2009; Trout & DeJonge, 2017). Yields initially increase approximately linearly with additional units of applied irrigation. Beyond a point, the marginal productivity of irrigation water use then declines as nonconsumptive losses (e.g., soil evaporation and deep percolation) from extra units of applied irrigation, until eventually plateauing (i.e., zero marginal productivity of irrigation) when crop water demands are fully satisfied. Note that if the production function was projected further to the right then the marginal value product of irrigation would eventually become negative due to the negative effects of waterlogging on crop development and yield formation.

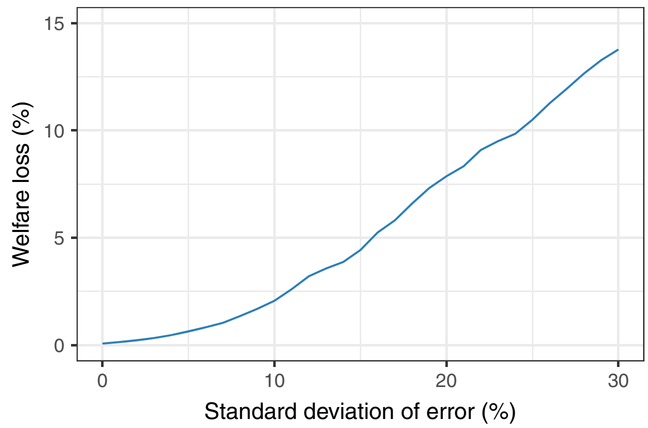

Figure 5. Relationship between the standard deviation of water use measurement error (%) and economic welfare loss to a farmer (%). Analysis assumes that errors are normally distributed with mean error of 0% and that baseline water use allocation is 450 mm. Welfare loss calculation use the production function shown in Figure 4 and assume a crop price of $190/tonne, irrigation cost of 0.75$/ha-mm, and fixed production costs of $1,200/ha consistent with typical crop production costs in the High Plains region of the United States (Klein et al., 2019)

The solid vertical line on Figure 4 represents a hypothetical regulatory constraint to irrigation rates. Water use measurement errors mean that the actual allocation of water to the farmer may in fact be greater or less than the intended limit, as illustrated, for example, by the black dashed lines in Figure 4. Where water use is overestimated, the farmer will be subject to a stricter than intended restriction on water use resulting in lower economic returns due to the reduction in crop yield. In contrast, if water use is underestimated, the farmer will be able to increase water use above the intended limit. Importantly, however, water use will not increase beyond the level that would maximize profits for the farmer, which may be less than the limit imposed if the magnitude of underestimation is large.

Imposing a normal distribution of water use allocations with mean equal to the intended water use constraint of 450 mm per year (i.e., average measurement error is 0), Figure 5 shows that farmers' economic returns decrease nonlinearly with increases in the magnitude of the water use measurement error even where measurement error is unbiased. Economic losses to a farmer occur due to the underlying functional shape of the crop-water production function (Figure 4) and associated profit function. Specifically, the shape of these functions means that marginal losses (reduced crop yield) from an overestimation of water use (resulting in a smaller actual pumping limit) exceed the marginal gains (increased crop yield) from an underestimation of water use (resulting in a higher actual pumping limit).

This result is not specific to the production function shown in Figure 4 or the imposed distribution of measurement errors. In the supporting information of the manuscript, we show theoretically that unbiased measurement errors will always lead to welfare losses for farmers due to Jensen's inequality. Specifically, Jensen's inequality states that the mean of a convex (concave) function of a variable is always greater (lower) than the function of the mean variable. In the context of the example presented here, this condition means that the average economic return from a distribution of variable water allocations with mean equal to the intended water allocation will always be less than the average economic return to the intended water allocation itself. The magnitude of welfare losses increases with the variance in the underlying measurement error and will be largest where measurement error affects farmers' with a high marginal value of water use. In particular, impacts of measurement error may be magnified significantly where overestimation of water use means farmers' are unable to satisfy minimum water needs to avoid crop failure. For example, partial or complete damage to perennial crops could result in very large economic losses, due both to the high value and large reestablishment costs of perennial crop production.

Measurement errors have impacts not only on farmers' economic returns but may also impact the performance of water management policies depending on the underlying policy goals in a given region. For example, measurement errors may have large impacts on the effectiveness of policies designed to manage short-term or acute impacts of irrigation abstractions. In groundwater irrigation systems, for example, short-term or spatially localized increases in pumping rates due to measurement errors could exacerbate significantly nonlinear externalities of pumping, such as streamflow depletion, well interference, or saline intrusion, that are key drivers of groundwater management in many regions worldwide (OECD, 2015). Similarly, for surface water irrigation, unintended spatial or temporal variability of abstractions may create acute water shortages for other downstream users and could have damaging impacts on freshwater ecosystems that depend on maintenance of instream flows at specific times of year as opposed to long-term average rates of water availability or storage (Stewart et al., 2020). In contrast, management of long-term regional aquifer depletion is likely to be minimally impacted or unaffected by measurement errors where errors are unbiased. This is because spatial or temporal variability in abstractions will not affect the ability to manage long-term depletion as groundwater storage responds approximately linearly to pumping, and over space and time water use will converge to the intended volumetric limit (e.g., to balance with long-term aquifer recharge).

Our analysis and the discussion above has explored the effects of measurement errors from a monitoring system that is unbiased. However, in practice, measurement errors may not always be unbiased. Monitoring approaches that consistently overestimate true water use are likely to lead to significant unintended economic losses for farmers, in particular where they affect users whose marginal value of water is high, leading to reduced trust, acceptability and sustainability and effectiveness of water use policies. Conversely, consistent underestimation of water use could allow farmers to overexploit water resources, limiting effectiveness of policies designed to manage social and environmental impacts of irrigation water use whether from groundwater or surface water. However, at present, measurement error properties (e.g., distribution, magnitudes, and biases) remain challenging to characterize given the lack of objective validation of satellite-based water use estimates in the literature (section 2.3) and limited accessibility of public disaggregated water use data sets for ground truthing (Foster et al., 2019; Zipper et al., 2019).

4. Implications for Use of Satellite Water Use Estimates in Agricultural Water Management and Policy

Our analysis has shown that, despite growing interest among researchers and policymakers, satellite-based estimates of irrigation water use remain highly uncertain, with potential for measurement errors to generate significant negative impacts on both farmer welfare and water resource sustainability. In this context, below we discuss potential opportunities and challenges for reducing uncertainties in satellite-based estimation of irrigation water use. Subsequently, we discuss how data provided by satellite remote sensing could be most effectively leveraged to support agricultural water use accounting and policy, with specific emphasis on considering trade-offs between monitoring accuracy and costs along with alternative uses of remote sensing in conjunction with in situ monitoring to enable improved accounting and management of irrigation water use.

4.1. Opportunities and Challenges Exist for Reducing Satellite-Based Measurement Errors

One of the key challenges associated with estimation of irrigation water use from remote sensing relates to the uncertainty in underlying estimates of key crop-water variables (e.g., ET and soil moisture) derived from satellite imagery (section 2.4). Several opportunities exist to improve the accuracy and reliability of irrigation water use estimation. For example, Fisher et al. (2017) outline how improvements in spatial and temporal resolution of thermal-infrared imagery could support improved accuracy of ET estimation at local scales across agricultural landscapes. Further improvements in ET estimation may also be possible to obtain through integration of thermal-infrared and microwave imagery, including leveraging land surface temperature (Holmes et al., 2015) and surface soil moisture (Purdy et al., 2018) data from microwave sensors that provide data independent of cloud cover.

Similar improvements in the accuracy of soil moisture-driven models could be achieved by leveraging recent and planned future advances in the spatial and temporal resolution of satellite soil moisture products, for example, through the Sentinel-1 mission (Abolafia-Rosenzweig et al., 2019; Brocca et al., 2018). At present, however, these data come at the cost of reduced temporal resolution that has been shown to reduce accuracy of irrigation estimation in synthetic experiments negating some of the benefits of improved spatial resolution of imagery (Abolafia-Rosenzweig et al., 2019). While Sentinel-1 may improve the underlying spatial resolution of soil moisture data, observations still only capture moisture signals in the near-surface (top 5–10 cm). Thus, where rapid drainage occurs to deeper soil layers—for example, as would be expected under large irrigation events—resulting depths of irrigation may be underestimated (Olivera-Guerra et al., 2020), with potential for uncertainty to be further compounded by imperfect knowledge of local soil hydraulic properties governing water fluxes and storage.

Improvements in the accuracy and resolution of ET or soil moisture monitoring may help to close some of the gaps between estimated and actual irrigation water use. However, a key challenge remains to convert satellite-based measurements of consumptive water use in to estimates of applied or abstracted water. Previous discussion (section 2.4.3) has highlighted the difficulties of quantifying local-level spatial and temporal heterogeneity in irrigation efficiency, which will not be addressed by improvements to spatial, temporal, or spectral resolution of satellite imagery alone. One alternative to address this issue would be to instead use satellite data as a tool to enforce restrictions or regulations pertaining to consumptive as opposed to applied water use. Consumptive use management has been proposed, in particular, to support management of long-term aquifer depletion in regions with intensive groundwater irrigation (Molle & Closas, 2020a), due to the fact that consumptive water use is equivalent to net extraction of water from an aquifer—that is, the amount of water removed from aquifer storage after accounting for return flows caused by inefficiencies in the application and conveyance of abstracted water to fields. As such, monitoring of consumptive use of groundwater could provide a potentially effective tool to sustainably balance agricultural water use with recharge rates and limit long-term storage depletion.

While a potential answer to some of the challenges associated with indirect satellite-based monitoring of agricultural water use, in particular in groundwater dominated systems, switching to consumptive use management is not a panacea solution. ET is estimated indirectly from satellite data and, as a result, will always be subject to some uncertainties even in regions such as North America with large field sizes and well-defined land use (Fisher et al., 2017; Senay et al., 2016). Moreover, even with continual improvements in the accuracy of ET estimates, quantifying consumptive irrigation water use still depends on reliable precipitation data that may not be available at plot scales even in densely monitored regions (Mourtzinis et al., 2017). Similarly, where groundwater and surface water are used conjunctively, or where an individual plot is served by multiple abstraction licenses, attributing rates of consumptive use to specific water rights and sources will also be challenging. Given that crop water needs in many regions are often met by a combination of groundwater and surface water (Pulido-Velazquez et al., 2016; Tsur & Graham-Tomasi, 1991), along with supplemental water supplied by rainfall (Fishman, 2018; Russo & Lall, 2017), this suggests that the accuracy of satellite-based estimation of consumptive water use may be constrained by a number of factors beyond the quality of remote sensing data and models alone.

A further challenge for use of satellite-based estimates of consumptive water use in policy is the validity of the assumption that return flow dynamics have negligible influence on the performance of water management strategies. While this may be true when seeking to manage long-term spatially aggregated changes in water availability (e.g., regional aquifer depletion), it neglects the important effects of variability in irrigation efficiencies and return flows on local short-term externalities of irrigation abstraction. For example, consider two farmers whose consumptive water use rates are identical but who differ in their level of irrigation efficiency. The farmer with the lower efficiency will need to pump a greater volume of water—although their long-term net extraction remains the same. Where groundwater is the main source of water for irrigation, additional pumping will result in greater short-term aquifer drawdown in and around the pumping well that may exacerbate short-term acute externalities of abstraction such as streamflow depletion (Palazzo & Brozović, 2014) or well interference (Perrone & Jasechko, 2017). Similar challenges also exist for surface water irrigation or conjunctive use of both groundwater and surface water. Time lags and spatial redistribution of return flows may alter short-term availability of water for downstream users (Speir et al., 2016; Velpuri et al., 2020), with negative consequences where timing of water supply is important for these users, such as for freshwater ecosystems that are highly sensitive to intraseasonal flow dynamics (Stewart et al., 2020).

4.2. Choice of Monitoring Approach Involves Trade-Offs Between Accuracy and Costs

The discussion thus far has highlighted that while opportunities exist to improve the accuracy of satellite-based irrigation water use estimation—whether through new satellite data and models or alternative approaches to water rights accounting—eliminating uncertainties completely is unlikely to be possible. Indeed, in situ metering itself is also subject to uncertainties even where meters are reliably calibrated, with potential for more substantial errors where meters are improperly maintained, affected by tampering, or where water use records are self-reported by farmers.

In this context, there is a need for further to evaluate the economic and hydrologic implications of different approaches for monitoring agricultural water use as a function of their accuracy, reliability, and costs. Our analysis suggests that measurement errors could have important negative implications for farmer welfare and effectiveness of water management strategies. However, accurate in situ metering is also costly to implement and maintain relative to indirect monitoring through satellite remote sensing, a factor that has contributed historically to the limited uptake and slow spread of metering in many regions (Balasubramanya & Stifel, 2020; Closas & Molle, 2018; Hoogesteger, 2018; Novo et al., 2015). Trade-offs therefore exist between improved monitoring accuracy versus higher costs of implementation (Escriva-Bou et al., 2020), which must be balanced in the context of management objectives and heterogeneity in both the value of water and impacts of abstraction on the environment and other water users.

In some cases, it may not be economically optimal, practically or politically feasible for a regulator to monitor all irrigation water users with perfect accuracy. Where no or very limited in situ metering of agricultural abstractions currently exists, monitoring via satellite remote sensing may offer a potential solution to measure water use across landscapes and enable targeted policy interventions to improve long-term sustainability of water resources and rural economies. However, whether or not use of such data will add value compared to alternative proxy measures of water use already available to decision makers (e.g., crop type data and energy meter records) remains unclear and should be assessed further in future research. In this context, we suggest that the value of satellite-based monitoring relative to other potential proxy measures of water use will depend upon the relative differences in measurement errors and externalities (hydrologic and economic) resulting from different types of imperfect monitoring. In contrast, where no other proxy measures of water use exist, the value of imperfect satellite-based monitoring will depend on the balance between welfare losses resulting from measurement errors, compared with the economic and environmental impacts of being otherwise unable to regulate abstractions due to the lack of alternative viable monitoring solutions.

Alternatively, a water management agency could seek to maximize the overall cost effectiveness of irrigation water management by implementing more accurate forms of monitoring (e.g., in situ meters) in conjunction with cheaper but less accurate solutions such as satellite remote sensing. Future research should seek to explore the potential benefits of using in situ meters to monitor and regulate water use solely in locations where the hydrologic or economic impact of measurement errors are large or nonlinear while relying on remote sensing or other proxy measures of water use in locations where the marginal impacts of any measurement errors are small. For example, in locations where water use restrictions are set at levels coinciding with the linear portion of the crop-water production function or where the hydrological externalities of pumping are largely linear, welfare losses and hydrologic externalities from measurement errors would likely be small so long as the overall distribution of errors was not biased. In these cases, use of lower cost methods such as satellite remote sensing might be a more economically efficient means of monitoring and managing agricultural water use. However, care should also be taken to not assume that remote sensing is a zero-cost solution for monitoring. While much satellite data are accessible for free, there are large costs associated with acquiring the technical resources and human capacity to translate satellite imagery in to estimates irrigated quantities, along with for implementation and enforcement of policies based on these estimates.

To complement evaluation of trade-offs between monitoring accuracy and costs, greater research attention is also needed to improve benchmarking of measurement errors from satellite-based approaches for water use estimation, including quantification of how errors vary across different measurement approaches, spatial and temporal scales, climatic conditions, and agricultural production systems. Such analysis would help to identify potential pathways, for example, through integration of thermal-infrared and microwave satellite products (Fisher et al., 2017; Zaussinger et al., 2019) or use of new higher-resolution satellite observations of ET fluxes (Aragon et al., 2018) and soil moisture (Vergopolan et al., 2020), for improving accuracy of satellite-based monitoring approaches and would also facilitate comparison with alternative indirect monitoring approaches, such as quantification of groundwater abstraction from existing monitoring of pump electricity consumption (Kinzelbach et al., 2016; Zekri, 2009). Crucially, improving standards of model validation will require researchers and policymakers to work with farmers to enable greater collection and sharing of in situ water use data due to the limited availability of disaggregated water use records at present in the public domain. This will require significant efforts to build trust and apply appropriate data privacy safeguards around use of such data for development and testing of remote monitoring approaches (Zipper et al., 2019), in particular given historic concerns and resistance to the deployment of in situ monitoring in many irrigated agricultural regions.

4.3. Remote Sensing Data as a Complement Rather Than Substitute to In Situ Monitoring

Our analyses in this paper have focused on the use of satellite remote sensing for quantifying agricultural water use, considering in particular the opportunities and challenges for water use estimation at plot or field scales to support water use management and regulation. However, it is important to recognize that other pathways exist through which satellite remote sensing can contribute to accounting of irrigation abstractions and support implementation of policies designed to sustainably manage agricultural water use.

First, remote sensing has already been demonstrated to be an effective and reliable tool for monitoring and mapping of irrigated areas. While some limitations to mapping remain, for example, in regions with significant cloud cover or small plot sizes (Ozdogan et al., 2010), the accuracy of satellite-based irrigated area estimates undoubtedly exceeds that of estimates of applied or consumptive use of irrigation. Regulation and accounting of agricultural water use based on irrigated areas could be an effective and efficient solution for managing water use where crop water demands are relatively homogeneous between fields reducing the need for expensive in situ metering or uncertain indirect estimation of abstraction or consumptive use rates. Indeed, some regions already adopt this approach as the primary mechanism for regulating agricultural groundwater use. For example, in the La Mancha region of Spain, restrictions on agricultural water use are enforced based on satellite-derived maps of crop irrigated areas and nonsatellite agronomic estimates of consumptive irrigation water use per unit crop area (Sanz et al., 2016). Likewise, in parts of France satellite monitoring of irrigated areas plays an important role in targeting spot checks of individual groundwater users (Rinaudo et al., 2012), in particular where information about water use provided to regulators is self-reported by farmers (Montginoul et al., 2016).

Satellite-based assessment could also play an important role in helping to support targeted spot-checking of self-reported water abstraction data. A significant cost of in situ monitoring for regulators—both in terms of time and financial resources—is the need to manually collect meter readings from a large number of distributed abstraction locations for which maintaining reliable records may be challenging (Closas & Molle, 2018; De Stefano & Lopez-Gunn, 2012; Hoogesteger, 2018). Recent improvements in real-time remote data transfer and IOT-based technologies offer a potential solution to reduce costs of real-time monitoring of in situ metering (e.g., Fernández-Ahumada et al., 2019; Zhao et al., 2017), although these systems have yet to been implemented on large scales within either developed or developing countries. Additionally, in-person spot checks remain essential to deter meter tampering or false reporting and to identify locations of unauthorized or illegal abstraction points. In this context, satellite-based estimates of irrigation water use could provide valuable information to help in identifying potential "cheating" of regulations, eliminating need for manual meter checks on all irrigation wells or identifying locations of potential unauthorized abstractions. For example, Holley et al. (2020) highlight the use of satellite-based assessments of irrigated areas in combination with water rights inventories for detecting potential locations of noncompliance with water use regulations in the state of New South Wales in Australia. Similarly, in the western United States, satellite-based ET data have recently been used to identify irrigated areas as part of adjudication over water compact allocations between Montana and Wyoming (Thompson Jr, 2019), while in Idaho satellite ET data have been adjudicate and enforce curtailment policies in the Snake River basin (Allen et al., 2007).

Finally, water use accounting based on Earth observation data has been widely proposed by major international agencies to support monitoring and management of water use in low-income or developing countries where little if any preexisting in situ data exists (Karimi et al., 2013; Van Eekelen et al., 2015; Vogels et al., 2020). Evidence from our meta-analysis suggests that accuracy of satellite-based estimation of agricultural water use in general increases when averaged over larger spatial or temporal scales. Remote sensing data could therefore provide useful information about aggregated irrigation water use dynamics to improve knowledge about catchment water budgets and help to guide larger-scale decision-making about water conservation and stewardship. However, our findings also suggest that assertions about the ability of Earth observation to monitor water use at disaggregated spatial and temporal scales with requirements for only limited in situ calibration and validation (e.g., Capdevila & Herrmann, 2019) should be treated with caution and risk creating overconfidence among policymakers and decision makers about capacity of satellite imagery to provide a quick fix to water data availability constraints in many developing countries. Remote sensing should not be seen as a substitute for improved in situ monitoring and failure to adequately acknowledge limitations and uncertainties risks creating policies that hinder rather than support sustainable and equitable water resource management.

5. Conclusions

A key constraint to water management and policy globally is the lack of reliable and accurate data on agricultural water abstractions, in particular for groundwater irrigation. Our analysis has shown that a growing body of research exists that seeks to leverage satellite remote sensing in order to address widespread gaps in in situ monitoring of agricultural water withdrawals from both groundwater and surface water sources. However, we find a systematic lack of evidence to support the assertion that such methods can capture and reliably reproduce spatial and temporal heterogeneity in observed irrigation water use. In particular, large errors are observed in satellite-based water use estimates at field or plot scales that are the primary spatial unit for water use management and regulation.

Our results show that water use measurement errors, which arise from uncertainties in both model inputs (e.g., satellite estimates of water fluxes and meteorological data) and process representation (e.g., irrigation efficiency), will lead to large welfare losses for farmers even where measurement errors are unbiased. Welfare impacts of measurement errors increase nonlinearly with the magnitude of the measurement error and, furthermore, have potential to significantly undermine the performance and effectiveness of water management policies. For example, externalities of irrigation water use may be exacerbated where measurement errors unintentionally enable farmers to exceed sustainable abstraction limits at times or locations where the impact of water use on the environment and other water users is large or nonlinear.

On the basis of these findings, we identify and highlight a number of priority areas to support efforts to close gaps in accounting and monitoring of agricultural water use. Further research is needed to refine existing satellite-based models of irrigation water use, leveraging opportunities exist to reduce uncertainties through improvements in the resolution, integration, and interpretation of satellite imagery. Critically, this research must be underpinned by greater focus on model validation, in particular when seeking to make estimates of irrigation water use at plot scales and in highly heterogeneous smallholder farming systems. Improved understanding about the errors and uncertainties in satellite-based water use accounting in turn would help to inform assessments of the trade-offs between accuracy and costs of indirect satellite monitoring versus direct in situ metering, including benefits of combining satellite and in situ technologies to deliver reliable accounting of agricultural water use that is the foundation for effective and sustainable water management.

Data Availability Statement

A summary of studies used to produce the meta-analysis presented in this paper is provided in Table S1 of the manuscript. The production function used to perform a welfare analysis of measurement errors is reported in Foster and Brozović (2018). The underlying code used to perform this analysis and a copy of the data given in Table S1 are available from Zenodo (doi.org/10.5281/zenodo.4079027).

Acknowledgments
T. F. was supported by the FutureDAMS project (grant code: ES/P011373/1) through the Global Challenges Research Fund from UK Research and Innovation (UKRI).

References

Aarnoudse, E., Bluemling, B., Qu, W., & Herzfeld, T. (2019). Groundwater regulation in case of overdraft: National groundwater policy implementation in north-west China. *International Journal of Water Resources Development*, *35*(2), 264–282.

Abolafia-Rosenzweig, R., Livneh, B., Small, E. E., & Kumar, S. V. (2019). Soil moisture data assimilation to estimate irrigation water use. *Journal of Advances in Modeling Earth Systems*, *11*, 3670–3690. https://doi.org/10.1029/2019MS001797

Abuzar, M., Whitfield, D., & McAllister, A. (2017). Farm level assessment of irrigation performance for dairy pastures in the Goulburn-Murray District of Australia by combining satellite-based measures with weather and water delivery information. *ISPRS International Journal of Geo-Information*, *6*(8), 239.

Al Naber, M., & Molle, F. (2017). Controlling groundwater over abstraction: State policies vs local practices in the Jordan Highlands. *Water Policy*, *19*(4), 692–708.

Allen, R. G., Tasumi, M., Morse, A., Trezza, R., Wright, J. L., Bastiaanssen, W., et al. (2007). Satellite-based energy balance for mapping evapotranspiration with internalized calibration (METRIC)—Applications. *Journal of Irrigation and Drainage Engineering*, *133*(4), 395–406.

Ambika, A. K., Wardlow, B., & Mishra, V. (2016). Remotely sensed high resolution irrigated area mapping in India for 2000 to 2015. *Scientific Data*, *3*(1), 1–14.

Anderson, R. G., Lo, M. H., Swenson, S., Famiglietti, J. S., Tang, Q., Skaggs, T. H., et al. (2015). Using satellite-based estimates of evapotranspiration and groundwater changes to determine anthropogenic water fluxes in land surface models. *Geoscientific Model Development*, *8*(10), 3021.

Aragon, B., Houborg, R., Tu, K., Fisher, J. B., & McCabe, M. (2018). CubeSats enable high spatiotemporal retrievals of crop-water use for precision agriculture. *Remote Sensing*, *10*(12), 1867.

Babbitt, C., Gibson, K., Sellers, S., Brozović, N., Saracino, A., Hayden, A., et al. (2018). *The future of groundwater in California: Lessons in sustainable management from across the west*. Sacramento, CA, USA: Environmental Defense Fund.

Balasubramanya, S., & Stifel, D. (2020). Water, agriculture & poverty in an era of climate change: Why do we know so little? *Food Policy*, 101905.

Battude, M., Al Bitar, A., Brut, A., Tallec, T., Huc, M., Cros, J., et al. (2017). Modeling water needs and total irrigation depths of maize crop in the south west of France using high spatial and temporal resolution satellite imagery. *Agricultural Water Management*, *189*, 123–136.

Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., Van Dijk, A. I. J. M., Weedon, G. P., et al. (2020). Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrology and Earth System Sciences*, *21*(12), 6201–6217.

Biggs, T. W., Marshall, M., & Messina, A. (2016). Mapping daily and seasonal evapotranspiration from irrigated crops using global climate grids and satellite imagery: Automation and methods comparison. *Water Resources Research*, *52*, 7311–7326. https://doi.org/10.1002/2016WR019107

Bretreger, D., Yeo, I.-Y., Quijano, J., Awad, J., Hancock, G., & Willgoose, G. (2019). Monitoring irrigation water use over paddock scales using climate data and Landsat observations. *Agricultural Water Management*, *221*, 175–191.

Brocca, L., Tarpanelli, A., Filippucci, P., Dorigo, W., Zaussinger, F., Gruber, A., & Fernández-Prieto, D. (2018). How much water is used for irrigation? A new approach exploiting coarse resolution satellite soil moisture products. *International Journal of Applied Earth Observation and Geoinformation*, *73*, 752–766.

Brozović, N., & Young, R. (2014). Design and implementation of markets for groundwater pumping rights, *Water markets for the 21st century* (pp. 283–303): Springer.

Butler Jr, J. J., Whittemore, D. O., Wilson, B. B., & Bohling, G. C. (2018). Sustainability of aquifers supporting irrigated agriculture: A case study of the High Plains Aquifer in Kansas. *Water International*, *43*(6), 815–828.

Calatrava, J., & Martínez-Granados, D. (2019). Water buybacks to recover depleted aquifers in south-east Spain. *International Journal of Water Resources Development*, *35*(6), 977–998.

Campos, I., Neale, C. M. U., Suyker, A. E., Arkebauer, T. J., & Gonçalves, I. Z. (2017). Reflectance-based crop coefficients REDUX: For operational evapotranspiration estimates in the age of high producing hybrid varieties. *Agricultural Water Management*, *187*, 140–153.

Capdevila, A. S., & Herrmann, S. M. (2019). *New avenues for remote sensing applications for water management: A range of applications and the lessons learned from implementation*. Washington, D.C., United States: The World Bank.

Cheema, M. J. M., Immerzeel, W. W., & Bastiaanssen, W. G. M. (2014). Spatial quantification of groundwater abstraction in the irrigated Indus basin. *Groundwater*, *52*(1), 25–36.

Closas, A., & Molle, F. (2018). Chronicle of a demise foretold: State vs. local groundwater management in Texas and the High Plains Aquifer System. *Water Alternatives*, *11*(3), 511–532.

De Stefano, L., & Lopez-Gunn, E. (2012). Unauthorized groundwater use: Institutional, social and ethical considerations. *Water Policy*, *14*(S1), 147–160.

Deines, J. M., Kendall, A. D., Butler, J. J., & Hyndman, D. W. (2019). Quantifying irrigation adaptation strategies in response to stakeholder-driven groundwater management in the US High Plains Aquifer. *Environmental Research Letters*, *14*, 44014.

Droogers, P., Immerzeel, W. W., & Lorite, I. J. (2010). Estimating actual irrigation application by remotely sensed evapotranspiration observations. *Agricultural Water Management*, *97*(9), 1351–1359.

Elnmer, A., Khadr, M., Allam, A., Kanae, S., & Tawfik, A. (2018). Assessment of irrigation water performance in the Nile delta using remotely sensed data. *Water*, *10*(10), 1375.

English, M. J., Solomon, K. H., & Hoffman, G. J. (2002). A paradigm shift in irrigation management. *Journal of Irrigation and Drainage Engineering*, *128*(5), 267–277.

Ershadi, A., McCabe, M. F., Evans, J. P., Chaney, N. W., & Wood, E. F. (2014). Multi-site evaluation of terrestrial evaporation models using FLUXNET data. *Agricultural and Forest Meteorology*, *187*, 46–61.

Escriva-Bou, A., McCann, H., Hanak, E., Lund, J., Gray, B., Blanco, E., et al. (2020). Water accounting in western US, Australia, and Spain: Comparative analysis. *Journal of Water Resources Planning and Management*, *146*(3), 4,020,004.

Fehri, R., Khlifi, S., & Vanclooster, M. (2019). Disaggregating SDG-6 water stress indicator at different spatial and temporal scales in Tunisia. *Science of the Total Environment*, *694*, 133766.

Fereres, E., & Soriano, M. A. (2007). Deficit irrigation for reducing agricultural water use. *Journal of Experimental Botany*, *58*(2), 147–159.

Fernández-Ahumada, L. M., Ramírez-Faz, J., Torres-Romero, M., & López-Luque, R. (2019). Proposal for the design of monitoring and operating irrigation networks based on IoT, cloud computing and free hardware technologies. *Sensors*, *19*(10), 2318.

Fisher, J. B., Melton, F., Middleton, E., Hain, C., Anderson, M., Allen, R., et al. (2017). The future of evapotranspiration: Global requirements for ecosystem functioning, carbon and climate feedbacks, agricultural management, and water resources. *Water Resources Research*, *53*, 2618–2626. https://doi.org/10.1002/2016WR020175

Fisher, J. B., Tu, K. P., & Baldocchi, D. D. (2008). Global estimates of the land-atmosphere water flux based on monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites. *Remote Sensing of Environment*, *112*(3), 901–919.

Fishman, R. (2018). Groundwater depletion limits the scope for adaptation to increased rainfall variability in India. *Climatic Change*, *147*(1-2), 195–209.

Fishman, R., Lall, U., Modi, V., & Parekh, N. (2016). Can electricity pricing save India's groundwater? Field evidence from a novel policy mechanism in gujarat. *Journal of the Association of Environmental and Resource Economists*, *3*(4), 819–855.

Foster, T., & Brozović, N. (2018). Simulating crop-water production functions using crop growth models to support water policy assessments. *Ecological Economics*, *152*, 9–21.

Foster, T., Brozović, N., & Butler, A. P. (2017). Effects of initial aquifer conditions on economic benefits from groundwater conservation. *Water Resources Research*, *53*, 744–762. https://doi.org/10.1002/2016WR019365

Foster, T., Gonçalves, I. Z., Campos, I., Neale, C. M. U., & Brozovic, N. (2019). Assessing landscape scale heterogeneity in irrigation water use with remote sensing and in situ monitoring. *Environmental Research Letters*, *14*(2), 024004.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., et al. (2015). The climate hazards infrared precipitation with stations—A new environmental record for monitoring extremes. *Scientific Data*, *2*(1), 150066.

García-Vila, M., & Fereres, E. (2012). Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. *European Journal of Agronomy*, *36*(1), 21–31.

Garrido-Rubio, J., González-Piqueras, J., Campos, I., Osann, A., González-Gómez, L., & Calera, A. (2020). Remote sensing-based soil water balance for irrigation water accounting at plot and water user association management scale. *Agricultural Water Management*, *238*, 106236.

Geerts, S., & Raes, D. (2009). Deficit irrigation as an on-farm strategy to maximize crop water productivity in dry areas. *Agricultural Water Management*, *96*(9), 1275–1284.

Gibson, J., Franz, T. E., Wang, T., Gates, J., Grassini, P., Yang, H., & Eisenhauer, D. (2017). A case study of field-scale maize irrigation patterns in western Nebraska: Implications for water managers and recommendations for hyper-resolution land surface modeling. *Hydrology and Earth System Sciences*, *21*, 1051–1062.

Gonçalves, I. Z., Mekonnen, M. M., Neale, C. M. U., Campos, I., & Neale, M. R. (2020). Temporal and spatial variations of irrigation water use for commercial corn fields in Central Nebraska. *Agricultural Water Management*, *228*, 105924.

Gonzalez-Dugo, M. P., Neale, C. M. U., Mateos, L., Kustas, W. P., Prueger, J. H., Anderson, M. C., & Li, F. (2009). A comparison of operational remote sensing-based models for estimating crop evapotranspiration. *Agricultural and Forest Meteorology*, *149*(11), 1843–1853.

Grafton, R. Q. (2019). Policy review of water reform in the Murray–Darling Basin, Australia: The "do's" and "do'nots". *Australian Journal of Agricultural and Resource Economics*, *63*(1), 116–141.

Hanemann, M., & Young, M. (2020). Water rights reform and water marketing: Australia vs the US West. *Oxford Review of Economic Policy*, *36*(1), 108–131.

Holley, C., Mutongwizo, T., Pucci, S., Castilla-Rho, J., & Sinclair, D. (2020). Groundwater regulation, compliance and enforcement: Insights on regulators, regulated actors and frameworks in New South Wales, Australia, *Sustainable groundwater management* (pp. 411–433): Springer.

Holmes, T. R. H., Crow, W. T., Hain, C., Anderson, M. C., & Kustas, W. P. (2015). Diurnal temperature cycle as observed by thermal infrared and microwave radiometers. *Remote Sensing of Environment*, *158*, 110–125.

Hoogesteger, J. (2018). The ostrich politics of groundwater development and neoliberal regulation in Mexico. *Water Alternatives*, *11*(3), 552–571.

Hunink, J. E., Contreras, S., Soto-García, M., Martin-Gorriz, B., Martinez-Álvarez, V., & Baille, A. (2015). Estimating groundwater use patterns of perennial and seasonal crops in a Mediterranean irrigation scheme, using remote sensing. *Agricultural Water Management*, *162*, 47–56.

Jalilvand, E., Tajrishy, M., Hashemi, S. A. G. Z., & Brocca, L. (2019). Quantification of irrigation water using remote sensing of soil moisture in a semi-arid region. *Remote Sensing of Environment*, *231*, 111226.

Javadian, M., Behrangi, A., Gholizadeh, M., & Tajrishy, M. (2019). METRIC and WaPOR estimates of evapotranspiration over the Lake Urmia Basin: Comparative analysis and composite assessment. *Water*, *11*(8), 1647.

Karimi, P., Bastiaanssen, W. G. M., & Molden, D. (2013). Water Accounting Plus (WA+)—A water accounting procedure for complex river basins based on satellite measurements. *Hydrology & Earth System Sciences*, *17*(7), 2459–2472.

Kinzelbach, W., Pedrazzini, G., & Wang, H. (2016). Managing overpumped aquifers—A road to sustainable water use. *International Journal of Water Resources and Arid Environments*, *5*(2), 134–143.

Klein, R., McClure, G., & Wilson, R. (2019). *2020 Nebraska Crop Budgets. Report no. EC872*. Lincoln, NE, United States: University of Nebraska-Lincoln Extension.

Kumar, S. V., Peters-Lidard, C. D., Santanello, J. A., Reichle, R. H., Draper, C. S., Koster, R. D., et al. (2015). Evaluating the utility of satellite soil moisture retrievals over irrigated areas and the ability of land data assimilation methods to correct for unmodeled processes. *Hydrology and Earth System Sciences*, *19*, 4463–4478.

Long, D., & Singh, V. P. (2013). Assessing the impact of end-member selection on the accuracy of satellite-based spatial variability models for actual evapotranspiration estimation. *Water Resources Research*, *49*, 2601–2618. https://doi.org/10.1002/wrcr.20208

López-Gunn, E. (2012). Groundwater governance and social capital. *Geoforum*, *43*(6), 1140–1151.

Lopez Valencia, O. M., Johansen, K., Aragon Solorio, B. J. L., Li, T., Houborg, R., Malbeteau, Y., et al. (2020). Mapping groundwater abstractions from irrigated agriculture: Big data, inverse modeling and a satellite-model fusion approach. *Hydrology and Earth System Sciences Discussions*. https://doi.org/10.5194/hess-2020-50

Lawston, P. M., Santanello, J. A. Jr, & Kumar, S. V. (2017). Irrigation signals detected from SMAP soil moisture retrievals. *Geophysical Research Letters*, *44*, 11,860–11,867. https://doi.org/10.1002/2017GL075733

MDMA (2017). *The Murray-Darling basin water compliance review: Containing reports by the Murray-Darling basin authority and the independent review panel*. Canberra, Australia: Murray-Darling Basin Authority.

Ma, Y., Liu, S., Song, L., Xu, Z., Liu, Y., Xu, T., & Zhu, Z. (2018). Estimation of daily evapotranspiration and irrigation water efficiency at a Landsat-like scale for an arid irrigation area using multi-source remote sensing data. *Remote Sensing of Environment*, *216*, 715–734.

Medellin-Azuara, J., Paw U, K. T., Jin, Y., Jankowski, J., Bell, A. M., Kent, E., et al. (2019). *A comparative study for estimating crop evapotranspiration in the Sacramento-San Joaquin Delta*. Davis, California, United States: University of California Davis.

Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E., & Houston, T. G. (2012). An overview of the global historical climatology network-daily database. *Journal of Atmospheric and Oceanic Technology*, *29*(7), 897–910.

Molden, D., & Sakthivadivel, R. (1999). Water accounting to assess use and productivity of water. *International Journal of Water Resources Development*, *15*(1-2), 55–71.

Molle, F., & Closas, A. (2020a). Groundwater licensing and its challenges. *Hydrogeology Journal*, *28*, 1961–1974.

Molle, F., & Closas, A. (2020b). Why is state-centered groundwater governance largely ineffective? A review. *Wiley Interdisciplinary Reviews: Water*, *7*(1), e1395.

Montginoul, M., Rinaudo, J.-D., Brozović, N., & Donoso, G. (2016). Controlling groundwater exploitation through economic instruments: Current practices, challenges and innovative approaches, *Integrated groundwater management* (pp. 551–581). London, UK: Springer, Cham.

Mourtzinis, S., Edreira, J. I. R., Conley, S. P., & Grassini, P. (2017). From grid to field: Assessing quality of gridded weather data for agricultural applications. *European Journal of Agronomy*, *82*, 163–172.

Msigwa, A., Komakech, H. C., Verbeiren, B., Salvadore, E., Hessels, T., Weerasinghe, I., & Griensven, A. (2019). Accounting for seasonal land use dynamics to improve estimation of agricultural irrigation water withdrawals. *Water*, *11*(12), 2471.

Novo, P., Dumont, A., Willaarts, B. A., & López-Gunn, E. (2015). More cash and jobs per illegal drop? The legal and illegal water footprint of the Western Mancha Aquifer (Spain). *Environmental Science & Policy*, *51*, 256–266.

OECD (2015). *Drying wells, rising stakes: Towards sustainable agricultural groundwater use*. Paris, France: OECD Publishing.

Olivera-Guerra, L., Merlin, O., & Er-Raki, S. (2020). Irrigation retrieval from Landsat optical/thermal data integrated into a crop water balance model: A case study over winter wheat fields in a semi-arid region. *Remote Sensing of Environment*, *239*, 111627.

Ozdogan, M., Yang, Y., Allez, G., & Cervantes, C. (2010). Remote sensing of irrigated agriculture: Opportunities and challenges. *Remote Sensing*, *2*(9), 2274–2304.

Palazzo, A., & Brozović, N. (2014). The role of groundwater trading in spatial water management. *Agricultural Water Management*, *145*, 50–60.
Parkes, B., Higginbottom, T. P., Hufkens, K., Ceballos, F., Kramer, B., & Foster, T. (2019). Weather dataset choice introduces uncertainty to estimates of crop yield responses to climate variability and change. *Environmental Research Letters*, *14*(12), 124089.
Peña-Arancibia, J. L., Mainuddin, M., Kirby, J. M., Chiew, F. H. S., McVicar, T. R., & Vaze, J. (2016). Assessing irrigated agriculture's surface water and groundwater consumption by combining satellite remote sensing and hydrologic modelling. *Science of the Total Environment*, *542*, 372–382.
Perrone, D., & Jasechko, S. (2017). Dry groundwater wells in the western United States. *Environmental Research Letters*, *12*(10), 104002.
Pulido-Velazquez, M., Marques, G. F., Harou, J. J., & Lund, J. R. (2016). Hydroeconomic models as decision support tools for conjunctive management of surface and groundwater. In A. J. Jakeman, O. Barreteau, R. J. Hunt, J. D. Rinaudo, A. Ross (Eds.), *Integrated Groundwater Management* (pp. 693–710). London, UK: Springer.
Purdy, A. J., Fisher, J. B., Goulden, M. L., Colliander, A., Halverson, G., Tu, K., & Famiglietti, J. S. (2018). SMAP soil moisture improves global evapotranspiration. *Remote Sensing of Environment*, *219*, 1–14.
Rad, M. R., Brozović, N., Foster, T., & Mieno, T. (2020). Effects of instantaneous groundwater availability on irrigated agriculture and implications for aquifer management. *Resource and Energy Economics*, *59*, 101129.
Rinaudo, J.-D., Montginoul, M., Varanda, M., & Bento, S. (2012). Envisioning innovative groundwater regulation policies through scenario workshops in France and Portugal. *Irrigation and Drainage*, *61*, 65–74.
Rinaudo, J.-D., Moreau, C., & Garin, P. (2016). Social justice and groundwater allocation in agriculture: A French case study, *Integrated groundwater management* (pp. 273–293): Springer, Cham.
Romaguera, M., Krol, M. S., Salama, M., Su, Z., Hoekstra, A. Y., et al. (2014). Application of a remote sensing method for estimating monthly blue water evapotranspiration in irrigated agriculture. *Remote Sensing*, *6*(10), 10,033–10,050.
Rouillard, J. (2020). Tracing the impact of agricultural policies on irrigation water demand and groundwater extraction in France, *Sustainable groundwater management* (pp. 461–479). London, UK: Springer.
Russo, T. A., & Lall, U. (2017). Depletion and response of deep groundwater to climate-induced pumping variability. *Nature Geoscience*, *10*(2), 105–108.
Santos, C., Lorite, I. J., Tasumi, M., Allen, R. G., & Fereres, E. (2010). Performance assessment of an irrigation scheme using indicators determined with remote sensing techniques. *Irrigation Science*, *28*(6), 461–477.
Sanz, D., Calera, A., Castaño, S., & Gómez-Alday, J. J. (2016). Knowledge, participation and transparency in groundwater management. *Water Policy*, *18*(1), 111–125.
Scanlon, B. R., Faunt, C. C., Longuevergne, L., Reedy, R. C., Alley, W. M., McGuire, V. L., & McMahon, P. B. (2012). Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. *Proceedings of the National Academy of Sciences*, *109*(24), 9320–9325.
Segovia-Cardozo, D. A., Rodríguez-Sinobas, L., & Zubelzu, S. (2019). Water use efficiency of corn among the irrigation districts across the Duero river basin (Spain): Estimation of local crop coefficients by satellite images. *Agricultural Water Management*, *212*, 241–251.
Senay, G. B., Friedrichs, M., Singh, R. K., & Velpuri, N. M. (2016). Evaluating Landsat 8 evapotranspiration for water use mapping in the Colorado River Basin. *Remote Sensing of Environment*, *185*, 171–185.
Shah, T. (2014). Groundwater governance and irrigated agriculture. Stockholm, Sweden: Global Water Partnership.
Sidhu, B. S., Kandlikar, M., & Ramankutty, N. (2020). Power tariffs for groundwater irrigation in India: A comparative analysis of the environmental, equity, and economic tradeoffs. *World Development*, *128*, 104836.
Smith, S. M., Andersson, K., Cody, K. C., Cox, M., & Ficklin, D. (2017). Responding to a groundwater crisis: The effects of self-imposed economic incentives. *Journal of the Association of Environmental and Resource Economists*, *4*(4), 985–1023.
Speir, C., Han, J., & Brozović, N. (2016). Spatial dynamic optimization of groundwater use with ecological standards for instream flow. *Water Economics and Policy*, *2*(03), 1,650,013.
Stewart, I. T., Rogers, J., & Graham, A. (2020). Water security under severe drought and climate change: Disparate impacts of the recent severe drought on environmental flows and water supplies in Central California. *Journal of Hydrology X*, 100054.
Thompson Jr, B. H. (2019). *State of Montana vs. state of Wyoming and state of North Dakota. Second Interim Report of the Special Master*. Washington, D.C., United States: Supreme Court of the United States.
Trout, T. J., & DeJonge, K. C. (2017). Water productivity of maize in the US High Plains. *Irrigation Science*, *35*(3), 251–266.
Tsur, Y., & Graham-Tomasi, T. (1991). The buffer value of groundwater with stochastic surface water supplies. *Journal of Environmental Economics and Management*, *21*(3), 201–224.
USDA (2019). *2018 irrigation and water management survey*. Washington, D.C., United States: USDA.
Van Eekelen, M. W., Bastiaanssen, W. G. M., Jarmain, C., Jackson, B., Ferreira, F., Van der Zaag, P., et al. (2015). A novel approach to estimate direct and indirect water withdrawals from satellite measurements: A case study from the Incomati basin. *Agriculture, Ecosystems & Environment*, *200*, 126–142.
Van Wart, J., Grassini, P., & Cassman, K. G. (2013). Impact of derived global weather data on simulated crop yields. *Global Change Biology*, *19*(12), 3822–3834.
Veldwisch, G. J., Venot, J. P., Woodhouse, P., Komakech, H. C., & Brockington, D. (2019). Re-introducing politics in African farmer-led irrigation development: Introduction to a special issue. *Water Alternatives*, *12*(1), 1–12.
Velpuri, N. M., Senay, G. B., Schauer, M., Garcia, C. A., Singh, R. K., Friedrichs, M., et al. (2020). Evaluation of hydrologic impact of an irrigation curtailment program using Landsat satellite data. *Hydrological Processes*, *34*(8), 1697–1713.
Vergopolan, N., Chaney, N. W., Beck, H. E., Pan, M., Sheffield, J., Chan, S., & Wood, E. F. (2020). Combining hyper-resolution land surface modeling with SMAP brightness temperatures to obtain 30-m soil moisture estimates. *Remote Sensing of Environment*, *242*, 111740.
Vogels, M. F. A., De Jong, S. M., Sterk, G., Douma, H., & Addink, E. A. (2019). Spatio-temporal patterns of smallholder irrigated agriculture in the horn of Africa using GEOBIA and Sentinel-2 imagery. *Remote Sensing*, *11*(2), 143.
Vogels, M. F. A., de Jong, S. M., Sterk, G., Wanders, N., Bierkens, M. F. P., & Addink, E. A. (2020). An object-based image analysis approach to assess irrigation-water consumption from MODIS products in Ethiopia. *International Journal of Applied Earth Observation and Geoinformation*, *88*, 102067.
Vuolo, F., Essl, L., & Atzberger, C. (2015). Costs and benefits of satellite-based tools for irrigation management. *Frontiers in Environmental Science*, *3*, 52.
Wester, P., Hoogesteger, J., & Vincent, L. (2009). Local IWRM organizations for groundwater regulation: The experiences of the Aquifer Management Councils (COTAS) in Guanajuato, Mexico. *Natural Resources Forum*, *33*, 29–38.
Woodhouse, P., Veldwisch, G. J., Venot, J.-P., Brockington, D., Komakech, H., & Manjichi, A. (2017). African farmer-led irrigation development: Re-framing agricultural policy and investment?. *The Journal of Peasant Studies*, *44*(1), 213–233.

Wu, X., Zhou, J., Wang, H., Li, Y., & Zhong, B. (2015). Evaluation of irrigation water use efficiency using remote sensing in the middle reach of the Heihe river, in the semi-arid Northwestern China. *Hydrological Processes*, *29*(9), 2243–2257.

Zaussinger, F., Dorigo, W., Gruber, A., Tarpanelli, A., Filippucci, P., & Brocca, L. (2019). Estimating irrigation water use over the contiguous United States by combining satellite and reanalysis soil moisture data. *Hydrology and Earth System Sciences*, *23*(2), 897–923.

Zekri, S. (2009). Controlling groundwater pumping online. *Journal of Environmental Management*, *90*(11), 3581–3588.

Zhang, K., Kimball, J. S., & Running, S. W. (2016). A review of remote sensing based actual evapotranspiration estimation. *Wiley Interdisciplinary Reviews: Water*, *3*(6), 834–853.

Zhao, W., Lin, S., Han, J., Xu, R., & Hou, L. (2017). Design and implementation of smart irrigation system based on LoRa, *2017 IEEE Globecom Workshops (GC Wkshps)* (pp. 1–6). Singapore, Singapore.

Zipper, S. C., Stack Whitney, K., Deines, J. M., Befus, K. M., Bhatia, U., Albers, S. J., et al. (2019). Balancing open science and data privacy in the water sciences. *Water Resources Research*, *55*, 5202–5211. https://doi.org/10.1029/2019WR025080

Zohaib, M., & Choi, M. (2020). Satellite-based global-scale irrigation water use and its contemporary trends. *Science of The Total Environment*, *714*, 136719.