Annual Irrigation Dynamics in the U.S. Northern High Plains Derived from Landsat Satellite Data

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Abstract  Sustainable management of agricultural water resources requires improved understanding of irrigation patterns in space and time. We produced annual, high-resolution (30 m) irrigation maps for 1999–2016 by combining all available Landsat satellite imagery with climate and soil covariables in Google Earth Engine. Random forest classification had accuracies from 92 to 100% and generally agreed with county statistics ($r^2 = 0.88–0.96$). Two novel indices that integrate plant greenness and moisture information show promise for improving satellite classification of irrigation. We found considerable interannual variability in irrigation location and extent, including a near doubling between 2002 and 2016. Statistical modeling suggested that precipitation and commodity price influenced irrigated extent through time. High prices incentivized expansion to increase crop yield and profit, but dry years required greater irrigation intensity, thus reducing area in this supply-limited region. Data sets produced with this approach can improve water sustainability by providing consistent, spatially explicit tracking of irrigation dynamics over time.

Plain Language Summary  Irrigated agriculture is the world’s largest consumer of global freshwater. In order to effectively use limited water supplies, managers need to understand when and where irrigation occurs. We fill this knowledge gap by using satellite images to produce annual maps of irrigation for 1999–2016 in a large, economically important agricultural region in the central United States that must manage its water supply for multiple users. We then used these maps to study changes in irrigation over time. We were surprised to find that the total area and individual locations of irrigated fields changed substantially from year to year. Our analysis suggests that farmers expanded irrigation when crop prices were high to increase crop yield and profit. We initially expected to also see increases in drought years to compensate for lack of rainfall, but instead, we found the opposite: irrigated area decreased in dry years.

Looking closer, we realized that this happened because farmers had to irrigate more heavily over each field, which reduced the number of fields they could irrigate due to limited water supply. These irrigation maps consistently track irrigation over time and are freely available for others to use to help manage water sustainably and meet food needs.

1. Introduction

Following rapid expansion in the late twentieth century, global irrigated area is now relatively stable (Wada et al., 2013). Regional gains and losses, however, can be substantial (Brown & Pervez, 2014). Dynamic crop prices, climate and precipitation variability, changing water policies, and crop rotations all drive considerable local interannual variability in irrigated area (Brown & Pervez, 2014; Ozdogan & Gutman, 2008; Wisser et al., 2008). Spatial irrigation data sets that accurately delineate irrigated areas annually would help constrain water budgets, improve hydrologic models, provide timely information to water managers and food security efforts, give insight into factors that influence irrigation behavior, and further clarify the effects of climate change on irrigation water demand and supply. Researchers have noted the need for routine mapping of irrigated lands (Brown & Pervez, 2014; Peña-Arcinieba et al., 2014; Teluguntla et al., 2017; Thenkabail & Wu, 2012), yet satellite-derived annual data sets are rare (Abuzar et al., 2015) due to historic computational limitations and inadequate ground reference data.

Quantifying temporal and spatial variations in irrigation is fundamental to the challenge of sustainable water management. Globally, irrigated agriculture accounts for approximately 70% of human freshwater use (Rosegrant et al., 2009; Wada et al., 2013). Irrigation greatly enhances agricultural yields (e.g., Smidt et al., 2016) and price stability, but overexploitation of water resources has depleted groundwater aquifers and reduced annual river discharge (Postel, 2003; Rockström et al., 2012). Moreover, incentives to expand...
irrigation continue to grow due to increased food demand (Tilman et al., 2011), agricultural intensification (Gleick, 2003), and climate change (Aleksandrova et al., 2014; Wada et al., 2013). Effectively managing limited water resources to meet future irrigation needs while remaining within regional and planetary boundaries of sustainable freshwater use (Rockström et al., 2012) is a major challenge.

Unfortunately, existing irrigation data sets are largely inadequate for this task, and the locations of irrigated areas remain uncertain (Ozdogan & Gutman, 2008; Peña-Arancibia et al., 2014; Wada et al., 2011; Wisser et al., 2008). Existing data sets are primarily based on administrative boundary statistics for irrigated area or land equipped for irrigation, which lack spatial precision and can contain self-reporting bias. Existing spatially explicit, satellite-derived data sets tend to have relatively low resolution (250–1,000 m), particularly at regional scales. Critically, the vast majority of data sets are generally single year, static snapshots that overlook temporal irrigation dynamics.

Notable exceptions include recent work mapping annual irrigation for 14 years in Afghanistan (Pervez et al., 2014) and 16 years in Australia (Teluguntla et al., 2017), which provided insights into temporal trends and variability in irrigation. For example, Pervez et al. (2014) found that irrigated area differed as much as 30% among years. Both studies were limited to the relatively coarse 250 m resolution of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite products due to reported computing constraints. Although moderate resolution efforts are sufficient to capture broad-scale patterns (Wardlow & Egbert, 2008), higher-resolution imagery such as those from Landsat satellites (30 m) better resolve smaller or fragmented fields, provide precise field locations, and increase accuracy (Velpuri et al., 2009). Due to the corresponding increase in data volume and processing requirements, however, Landsat-based annual data sets are rare and limited to local studies. For example, Ozdogan et al. (2006) produced nine annual 30 m maps for a 1,500 km² area in Turkey using one Landsat scene per year. Irrigation dynamics compared across these early efforts in annual mapping differ in overall trend, yearly variance, and contextual drivers, suggesting that annual, spatial data sets offer a refined picture of regional irrigation differences not well captured by static maps or aspatial data.

Here we produced high-resolution, annual irrigation maps from 1999 to 2016 across the greater Republican River Basin region in the central United States (Figure 1), hereafter termed the Annual Irrigation Maps-Republican River Basin (AIM-RRB) data set (available at http://dx.doi.org/10.4211/hs.55331a41d5f34c97ba90be910af070). We leveraged recent developments in cloud computing to utilize all available Landsat scenes each year, combining satellite imagery with climate and soil covariables in a random forest classification workflow that is readily applicable to future years for ongoing monitoring. Research using the full Landsat record is a relatively recent phenomenon (e.g., Hansen et al., 2013) and to our knowledge not previously applied to irrigation mapping. We then used these maps to examine irrigation dynamics and associated drivers across this region.

2. Methods
2.1. Study Area
The Republican River Basin (RRB) overlies portions of Colorado, Nebraska, and Kansas, draining a large portion of the High Plains Aquifer (HPA) before leaving the aquifer near the downstream Nebraska-Kansas border (Figure S1 in the supporting information). The basin provides riparian surface water irrigation and groundwater irrigation over the HPA. Annual cropping systems dominate the region, and the top five crops by area planted (wheat, corn, soy, alfalfa/hay, and sorghum) can be irrigated or rainfed (Figure S2). Due to litigation concerning interstate water use beginning in 1999, both groundwater and surface water irrigation are regulated to preserve streamflow into Kansas in accordance with the Republican River Compact of 1942. Strategies to meet streamflow targets vary widely across localized management districts, change over time, and include restrictions on pumping volume, well-drilling moratoriums, efforts to retire water rights, and expensive augmentation plans via engineered water transfers (see Griggs, 2017 for further discussion). The Republican River Compact Administration assesses compliance with a groundwater model covering the groundwatershed upstream of Kansas (Republican River Compact Administration (RRCA), 2003), an area hereafter termed the RRCA. Therefore, our study domain is the 86,429 km² greater Republican Basin (GRB), defined as the union of the RRCA and RRB (Figures 1 and S1). Annual irrigation maps and accuracy metrics are produced with a minimum 10 km buffer (total area: 141,603 km², Text S1), though map results are presented solely for the GRB. In addition, we analyzed irrigation drivers in the portion of the RRB contained.
within the RRCA (RRB-RRCA) for 1999–2015 to capitalize on irrigation water volume data from the groundwater model (section 3.3). We defined the crop year as 1 November to 31 October to ascribe greenness from winter wheat to the year harvested. Mean annual precipitation increases eastward along a longitudinal gradient, ranging from 341 to 845 mm during the study period. Growing season precipitation (1 December to 31 August) ranged from 284 to 673 mm (Abatzoglou, 2013).

2.2. Satellite Imagery, Vegetation Indices, and Environmental Variables

Landsat imagery is provided at nominal 30 m resolution in ~175 × 185 km scene tiles, 16 of which overlie the buffered study region (Figure S3). Working in Google Earth Engine’s (GEE) cloud computing platform (Gorelick et al., 2017), we used all available Landsat Surface Reflectance Products (U.S. Geological Survey (USGS), 2017a, 2017b) from 1 November 1998 to 31 October 2016 (9,592 scenes, Text S2), as temporal resolution increased substantially in 1999 after Landsat 7 came online and image acquisition improved (Pekel et al., 2016). Concurrently operating Landsat satellites provided an 8 day overpass interval for all years except 2012, when only Landsat 7 was operational. This 8 day interval was simultaneously augmented by side-overlapping scene edges and reduced by clouds and acquisition inconsistencies, resulting in 99% of pixels having between 12 and 64 satellite observations per year except 2012 (mean including 2012: 28). This provided adequate temporal resolution to capture both baseline and peak greenness for multiple crop calendars (Figure 2a). Detailed information about Landsat scenes, processing, and yearly statistics for pixel observation frequency can be found in Text S2 and Figure S4.

Figure 1. Study area location and map of irrigation frequency. (a) Study area (purple) in the context of the High Plains Aquifer (blue). (b) Number of years each 30 × 30 m map pixel was classified as irrigated between 1999 and 2016 across the Republican River Basin (dashed outline) and the associated Republican River Compact Administration’s (RRCA) groundwater model (solid outline), with zoomed inset for enhanced resolution. Annual irrigation maps also demarcate novel and deactivated irrigated areas as demonstrated by mapping (c) earliest and (d) latest years irrigated during the study period.
In GEE, we produced composites of annual maximum and annual range for four vegetation indices: (1) the normalized difference vegetation index (NDVI); (2) the enhanced vegetation index (EVI); (3) the normalized difference water index (NDWI), which is sensitive to plant water content (Gao, 1996); and (4) a less common green index (GI) (Gitelson et al., 2005) that is particularly sensitive to irrigation status (Ozdogan & Gutman, 2008). Text S3 provides detailed index calculations. Composites thus captured both peak growing season greenness and the magnitude of annual change per pixel regardless of crop phenology.

Climate, soil, and slope information can improve classification accuracy by refining cases of potential irrigation and providing context for vegetation greenness. We assembled variables related to plant growth including precipitation, plant available water, slope, and aridity (Text S4). We also developed two novel combination indices that integrate moisture information with greenness levels to exaggerate differences by irrigation status and facilitate regional-scale classification across climate gradients. We called these the water-adjusted green index (WGI), calculated from Landsat as NDWI * GI, and aridity-normalized green index (AGI), calculated as GI / growing season aridity derived from meteorological data. In total, we generated 9 Landsat variables and 11 covariables for use in machine learning classification (Table S1).

### 2.3. Training Data

We developed a robust training data set using high-resolution (1 m) aerial imagery (National Agriculture Imagery Program, 2017), Landsat GI and EVI times series (Text S5), and crop-type maps (Cropland Data...
2.4. Classification

We used the full training data set to train both Classification and Regression Tree (CART) and random forest
(Breiman, 2001) classifiers in GEE. A random forest classifier with 500 trees that omitted rainfall soy training
points performed best on validation data used to evaluate classifiers (see Text S6). We applied the classifier to
the 1999–2016 period after masking urban, forest, and wetland areas using National Land Cover Database
maps (Fry et al., 2011). We did not mask other noncrop areas because this inhibited classification of dynamic
irrigation changes among years.

Following initial classification, we performed two cleaning operations: (1) a $3 \times 3$ majority filter and (2)
removal of pixels irrigated only once during the 18 year period, since infrastructure requirements make
single-year irrigation unlikely. To understand the relative contribution of input variables to classification
accuracy, we ran permutation tests and GINI Index metrics in R (R Core Team, 2014) with an identically
parameterized classifier since GEE did not output variable importance measures at the time of this study
(Text S7).

2.5. Accuracy Assessment and Analyses

Assessing multiyear classification efforts across large regions is challenging since limited ground truth data
are available. We sought to evaluate accuracy with test data sets across a wide range of years from multiple
data sources. First, we used two sets of national county statistics for six years (2002, 2007, 2012: NASS
Agricultural Census (NASS, 2017); 2000, 2005, 2010: USGS water use data (USGS, 2015)) to compare total irri-
gated area for 35 counties contained within the buffered GRB. Second, we randomly generated points across
Nebraska in 2002 and the full study area in 2015 (Figure S6) and marked them as “irrigated” or “not irrigated”
as described for training points. Cases where no clear determination could be made (24 of 2266 points) were
marked as “uncertain” and omitted from accuracy assessments. We chose 2002 (dry year) and 2015 (wet year)
to include all three Landsat sensors and two precipitation extremes in our assessment. Table S3 gives point
breakdowns among years and classes. We then analyzed annual maps to provide summary statistics of irri-
gated area, overall and regional trends, and exploratory analyses of irrigation drivers.

2.6. Data Limitations

Although we leveraged several GIS, satellite, and aerial imagery data sets, our method relied on manually
produced training and test data sets well suited to identify areas where irrigation clearly enhances greenness.
Locations where irrigation may have more subtle effects on greenness, such as subirrigation or where limited
irrigation is used to prevent crop failure, were not selected. AIM-RRB could therefore be described as a map of
“certainly irrigated” locations but may underrepresent some marginal irrigation areas.

3. Results and Discussion

The random forest classifier using all available Landsat scenes produced 18 annual irrigation maps from 1999
to 2016 (AIM-RRB). Figure 1b shows the number of years each pixel in the study region was classified as irri-
gated during these 18 years. We found that 24.3% of the GRB was irrigated at some point during the study
period, and of that area, 28.1% was perennally irrigated, which we defined as having irrigation over 80% of
years to allow for periodic crop rotations and fallowing. Only 8.4% of irrigated land was classified as irri-
gated for the entire study period. In general, perennial irrigation was concentrated near major rivers (Platte
and Republican, Figure S1) and in well-established groundwater areas. Nonperennial irrigation includes
irrigated fields added, deactivated, or intermittently rainfed/fallowed during the study period (see 3.2).
Figures 1c and 1d demonstrate how AIM-RRB can resolve years in which irrigation of individual fields began
and/or ceased. As this zoomed area highlights, irrigated areas were both added and deactivated throughout
the study period.

3.1. Classification Performance
Qualitatively, there was good visual agreement between Landsat composites, AIM-RRB, and previously
published USGS MIrAD-US products at lower resolution (250 m) for 2002, 2007, and 2012 (Brown & Pervez,
2014; Pervez & Brown, 2010) (Figure 2b). Using our point test data set, we found overall accuracies of
98.6% and 97.6% for 2002 and 2015, respectively. For the irrigated class, we had omission errors from 6.1
to 7.6% and commission errors from 0 to 6.3%. Table S3 shows a full breakdown of accuracy by class type
for 2002 and 2015.

County level comparisons with NASS and USGS irrigation statistics showed good agreement with AIM-RRB
estimates (Figure S7). We found $r^2$ values between 0.88 and 0.96 for the six available years, with similar agree-
ment between years used to train the classifier (2010 and 2012) and nontraining years as well as robust
performance across high and low precipitation years. AIM-RRB slightly underestimated irrigated area per
county compared to the county statistics, which can be seen in relation to the 1:1 lines in Figure S7. USGS
data are derived from state-specific statistical models with associated uncertainties, so it remains unclear if
AIM-RRB underestimates irrigation or if USGS estimates are high. NASS census data are self-reported but
anonymized to minimize inaccurate reporting. However, there may be underlying incentives to report
inflated numbers to preserve water rights. Alternatively, NASS may better reflect partial irrigation while
AIM-RRB likely favors fully irrigated fields (see 2.6). Finally, the Landsat data set likely missed peak greenness
in some locations due to cloud cover, resulting in occasional maximum greenness values similar to nonirri-
gated cropland. Because the MIrAD-US methodology uses the NASS county area statistics to allocate pixels
to the irrigated class, AIM-RRB is the only independent multiyear data source in the region.

3.1.1. Variable Importance
Our novel AGI and WGI indices, which combine GI with moisture indicators, ranked highest for both impor-
tance metrics used (permutation test: AGI; GINI Index: WGI; Text S7 and Figure S8). GI contributed to the top
three variables identified through both metrics, supporting previous findings that GI is more sensitive to
irrigation status than conventional indices such as NDVI and EVI (Ozdogan & Gutman, 2008; Ozdogan et al.,
2010). The annual GI range scored higher than maximum GI for both metrics, suggesting that the change
in greenness over the year conveys more information than peak greenness alone, corroborating conclusions
in Ozdogan et al. (2010). Interestingly, no climate-related variables ranked in the top eight according to the
GINI Index, despite the high relative importance of AGI in the permutation test. Climate-related variables may
gain importance for continental-scale applications with larger climatic ranges. Slope and soil-related
variables scored lowest, indicating that they do not enhance accuracy in this region. The high importance
of AGI and WGI suggests that these indices warrant further study for use in irrigation classification in other
agricultural regions.

3.2. Irrigation Trends
Irrigated area in the GRB increased during the study period at an average rate of 0.37% per year ($r^2 = 0.72,$
$p < 0.0001$, Figure 3a), with a lower rate of 0.26% for the more regulated RRB-RRCA subdomain ($r^2 = 0.62,$
$p < 0.0001$; Figure 4a). We found considerable variability around this trend, including multiple years in which
irrigated area decreased from the previous year. The range in irrigated area among years was large; for
example, irrigated area in the GRB increased by 92% between the low in 2002 and the high in 2016. Given
this variability, data sets lacking high temporal frequency could generate disparate conclusions based on
the years sampled. For example, a 5 year product such as MIrAD-US, which is based on NASS data for
2002, 2007, and 2012, would suggest a nonsignificant 0.02% increase per year for the GRB ($p = 0.90$).

Linear regression of irrigated area over time by 4 km$^2$ aggregated grid cells revealed that the highest rates of
increase were concentrated in the eastern, nonaquifer region and near the Platte and Republican Rivers,
while western groundwater-dominated regions had relatively flat to decreasing trends (Figure 3b). This is
likely due to groundwater allocation reductions, expanded well-drilling moratoriums, and retirement of water
rights in Nebraska and Colorado to comply with the Republican River Compact. These efforts to protect
streamflow have perhaps enabled the expansion of irrigation evident in the lower Kansas RRB (Figures 3a and 3b). Irrigated area was both added and deactivated across the study region (Figure 3a). Surface water-dominated regions such as the lower Kansas RRB deactivated negligible irrigated area over the study period but did suffer large temporary reductions in irrigated area during drought years such as 2012. Groundwater-dominated regions such as the CO RRB and the KS RRCA were less perturbed by drought but had the lowest net gain in novel irrigated areas (novel-deactivated area). Changes in total irrigated area not accounted for by net gains or losses likely were due to reduced dryland crop rotations and/or reduced fallowing frequency in existing irrigation areas.

3.3. Drivers of Irrigated Area

Spatiotemporal irrigation dynamics detailed in AIM-RRB result from farmer irrigation decisions made within the context of annual climate variation, crop commodity prices, water management, and water supply. Utilizing irrigation water volume estimates from the RRCA model for 1999–2015 (Figure 4b) (RRCA, 2003), we investigated how these drivers might interact to influence irrigation within the RRB-RRCA. Correlation

Figure 3. Subregional irrigation trends. (a) Irrigated area (black) by region. Spatial locations of each region are depicted in map backgrounds (dark gray). Cumulative novel area (red) summarizes newly irrigated pixels each year (2002–2015); cumulative area deactivated (blue) tracks pixels not irrigated in subsequent years (2000–2013). Omitted years buffered against consecutive fallow periods at the study period start or end. (b) Rate of change over time from linear regression. Cells with nonsignificant trends ($\alpha \geq 0.05$) are in gray.
matrices revealed that irrigated area was positively correlated with the previous year's crop prices ($r = 0.55$, $p = 0.02$) but not with precipitation, irrigation volume, or current year price (Figure S9a). Instead, irrigated area likely was linked to precipitation through the depth of irrigation water applied, calculated as irrigation water volume divided by area. Both irrigation water volume and irrigation depth had strong negative correlations with precipitation ($r = -0.89$ and $-0.86$, respectively; $p < 0.0001$). In years with low precipitation, such as the 2002 and 2012 droughts, irrigation volume and depths were elevated while irrigated area was reduced (Figures 4a, 4b, and 4e), indicating that farmers irrigated more intensely over less area to compensate for lack of rainfall. The inability to maintain or even expand irrigated area during dry periods when yield advantages are greatest suggests that farmers are limited in water supply, access rights, or delivery capability (e.g., Foster et al., 2014). Without complementary data sets on irrigation volume and spatial extent made possible by annual map products, it is not possible to discern if increased water use was due to areal expansion, application depth increases, or both.

Figure 4. Irrigated area over time and associated drivers. For the portion of the Republican River Basin overlying the High Plains Aquifer (RBB-RRCA, shown in dark gray in the map inset of the Greater Republican Basin study area): (a) Percent irrigated area from AIM-RRB. Rate of change (m) is given in percent and actual area. (b) Irrigation water volume (RRCA, 2003). (c) Precipitation from December 1 to August 31 (Text S3) (Abatzoglou, 2013). (d) Corn price in 2016 dollars (NASS, 2017). (e) Linear regression of irrigation application depth (volume / area) versus precipitation. (f) Trends in irrigated area versus precipitation for years with high and low prices (split determined from CART (Text S5 and Figure S9)).
Commodity prices also influence irrigation decisions by determining the return on investment for irrigation use. Corn price approximately doubled between 2003 and 2012 (Figure 4d). CART analysis suggested that price and precipitation interacted to influence annual irrigation extent (model $R^2 = 0.78$, Text S8 and Figure S9b). When price was low, irrigated area was low regardless of precipitation, likely due to poor return on irrigation costs (Figure 4f). In contrast, high prices incentivized irrigation expansion but was modulated by annual precipitation; low precipitation years required increased irrigation water depth ($r^2 = 0.72$, Figure 4e), limiting the amount of water available for areal expansion.

Although quantification is outside the scope of this paper, policy, management decisions, and groundwater depletion (e.g., Basso et al., 2013; Cotterman et al., 2017) also influence irrigation dynamics. This can include efficiency incentives and/or technological improvements that can increase area per unit volume, new use restrictions reducing irrigated area or, conversely, areal expansions in anticipation of future regulation (Pervez & Brown, 2010).

4. Conclusions

Our approach produced annual irrigation maps that provide consistent, spatially explicit tracking of irrigation, revealing temporal dynamics even in this heavily regulated system. Our use of the full Landsat record for each year allowed us to capture peak greenness values for multiple crops despite asynchronous crop maturation schedules and to quantify the annual range in greenness. We developed two new indicators combining remotely sensed plant greenness with moisture information (WGI and AGI) that show promise for improving satellite classification of irrigation. Because our approach utilizes satellite and derived climate data sets made available in near real time through Google Earth Engine, it can be applied to future years immediately following the growing season to provide updated and timely information to managers and scientists. The approach is transferable to other nonhumid regions dominated by annual crops given region-specific training data. These annual maps provide critical insight into behavioral responses to irrigation drivers and document annual irrigation dynamics with high precision, thus providing vital information to inform agricultural water use models and management decisions.

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