ASSESSING IRRIGATION TRENDS IN THE HIGH PLAINS AQUIFER REGION: COMPARING IRRIGATION TRENDS AND MAPPING EFFICIENT IRRIGATION USE

By

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ABSTRACT

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Irrigation is the primary consumptive user of water globally. Most of the land across the High Plains region in the United States is used for farming. Although irrigation is vital to prospering agricultural production, many states in the region only collect information about where, when, and how irrigation is implemented on coarse spatial levels through self-reported surveys. Recently, efforts have been made to further quantify irrigation through the classification of satellite imagery. Here, we address the differences and similarities between three most used reports of irrigation nationwide and one high resolution remotely sensed irrigation dataset (Deines et al., 2019) by applying fundamental statistical analyses to assess irrigation trends through time and to understand how they are impacted by outside drivers.

We then address the unknown question of how farms are irrigated by creating a farm-level dataset of efficient sprinkler irrigation adoption across the High Plains Aquifer region from 1990 to 2012. We apply a change point detection method across the region followed by a significance filter to identify characteristic changes in irrigation patterns that are likely associated with the adoption of efficient sprinkler irrigation systems. A validation of adoption decisions showed 87% accuracy on the farm-level in Kansas, which is the only state where validation data is readily available at the scale of individual points of diversion. Irrigation adoption trends are sufficiently identified through this method. Although limitations exist, these joint methods have excellent potential to further improve our knowledge of irrigation practices on a regional level to better inform decision-making and move towards sustainable farming practices.

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KEY TO ABBREVIATIONS

AIM	Annual Irrigation Maps–High Plains Aquifer (AIM–HPA, Deines et al., 2019)
ANOVA	Analysis of Variance
CHP	Central High Plains Aquifer
EQIP	Environmental Quality Incentives Program
HPA	High Plains Aquifer
LEPA	Low-Energy Precision Application
LESA	Low-Elevation Spray Application
LPIC	Low-Pressure in Canopy
MESA	Mid-Elevation Spray Application
NASS	National Agricultural Statistics Service
NHP	Northern High Plains Aquifer
SHP	Southern High Plains Aquifer
USGS	United States Geological Survey
USDA	United States Department of Agriculture
WIMAS	Water Information Management and Analysis System in Kansas

CHAPTER 1:
ASSESSING IRRIGATION TRENDS IN KANSAS: COMPARING SATELLITE-DERIVED AND SURVEY DATA

Abstract

Irrigation is the primary consumptive user of water globally, and studies have been done to identify where irrigation occurs and how it changes through time. In the High Plains region of the United States, most of the land is used for farming. Although irrigation is vital to maintain high levels of agricultural production there, many states in the region only collect irrigated area information on coarse spatial and temporal levels through self-reported surveys. Recently, efforts have been made to further quantify irrigation through the classification of satellite imagery. Here, we address the differences and similarities between three most used reports of irrigation nationwide and a high-resolution remotely sensed irrigation dataset (Deines et al., 2019). We apply fundamental statistical analyses to assess irrigation trends through time reported by each source. We then interpret how each of these reported irrigation datasets correlate with potential external drivers of irrigation. Through our methods, we show that survey data, although consistent and powerful, may not reflect the variability in farmer behavior and agricultural management practices as well as remotely sensed data. Although limitations exist in the simplified comparisons of the data, this study shows the potential future effects of using remotely sensed, spatially-explicit irrigated patterns to provide a foundation for improved policy and decision-making rather than relying solely on survey-reported irrigation information alone.

1. Introduction

Throughout history, irrigation has helped close the gap between water supply and crop water demand over space and time while also increasing agricultural yields (I. Carruthers et al., 1997; Schultz et al., 2005). Today, around 70% of freshwater withdrawals and 90% of consumptive freshwater use are attributed to irrigation worldwide (FAO, 2011; Shiklomanov, 2000). Unfortunately, projections show that to sustain or increase food production, water management techniques need to adapt (Molden, 2013). Farming management practices are often driven by policies, which ideally are written to solve problems identified by data analysis. Although many sources of self-reported survey data exist regarding irrigated area and water use, uncertainties in these data can lead to counterintuitive or unrealistic policies (Kendy et al., 2003; Pfeiffer & Lin, 2014; F. A. Ward & Pulido-Velazquez, 2008). In water-stressed areas of developed countries, adopting efficient irrigation technologies and allocating water withdrawals have already been implemented, yet these changes are not enough to offset the limited availability of freshwater. Irrigated area is expected to increase in the coming decades across the United States and worldwide (Faurès et al., 2002; McDonald & Girvetz, 2013).

In the United States (US), about 60% of the water used for irrigation is sourced from groundwater (Maupin & Barber, 2005; Siebert et al., 2010). Located in the central US, the High Plains Aquifer is one of the most exploited groundwater sources for irrigation, and is thus experiencing excessive withdrawal and depletion (Maupin et al., 2014; Wada et al., 2010). Irrigation sourced from groundwater is a nearly ubiquitous farming practice in this region because of the climate and resultant yield benefits. The United States depends on this intensely irrigated region to contribute to the agricultural production, as farming in this region accounted for almost 12% of the market value of agricultural products in the United States in 2007 even though the region only covers 5% of the total US land area (NASS, 2017; Bridget R Scanlon et al., 2012). Therefore, the long-term sustainability of the High Plains Aquifer (HPA) is paramount to agricultural production in the US.

In response to unsustainable depletion of the aquifer, many policies and incentives have been implemented to promote sustainable farming practices in the HPA (Dagnino & Ward, 2012; Wallander & Hand, 2011). These policies are informed by analyses and interpretations of publicly available data. Historically, an important source of agricultural survey data nationwide has been the Census of Agriculture, which is collected by the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA). Collected every five years, this survey provides important information such as irrigated area by county across the nation (USDA NASS, 2017). Higher spatial- and temporal-resolution data from the Kansas Water Information Management and Analysis System (WIMAS) contains farmer-reported irrigated area and irrigated water use at the point of diversion (e.g., well) level in Kansas (Wilson et al., 2005). Both sources contain important information about irrigated area and water use that has informed water management policies and conservation initiatives. Although these farmer-reported sources have been important for decision-making and model validation, survey data must be used with caution (Assael & Keon, 1982; Dalenius, 1977; Lessler & Kalsbeek, 1992; Reist et al., 2019). Data collected by survey sources has inherent problems such as non-response bias (Dalenius, 1977) or measurement error — the discrepancy between a participant's response and their behavior (Groves, 1987). Although measurements have been taken to minimize these problems, surveys depend on human behavior and participation, which is very difficult to predict or counteract.

Improvements in satellite-based imaging over the last 20 years has opened-up the opportunities to collect remotely sensed agricultural information. As opposed to survey data, irrigation patterns identified by satellites do not have inherent human bias. Satellite observations of farmland can tell us when and how much land was irrigated by classifying the qualities of vegetation such as greenness (Brown & Pervez, 2014; Ozdogan et al., 2010; Xu et al., 2019). Irrigation maps from satellite imagery started with coarse spatial resolution (10 km to 500 m) and only provided information for a small amount of years (Biggs et al., 2006; Gumma et al., 2011; P. S. Thenkabail, 2006). Recently, the public availability of higher spatial resolution imagery at shorter time windows over a long span of years has prompted an increase in irrigation mapping via classification of satellite imagery (Deines et al., 2017, 2019, 2021; Woodcock et al., 2008; Xu et al., 2019; Zhu et al., 2019). In this study, we analyze remotely-sensed Annual Irrigation Maps (AIM-HPA or AIM hereafter, Deines et al., 2019) that indicate irrigated area from over three decades across the High Plains Aquifer region at 30 m resolution. Remotely sensed data also have limitations including: lack of full-coverage imagery, sensor resolution, and sensitivity to weather conditions such as clouds and changes in precipitation (Moran, Inoue, and Barnes 1997; Ram and Kolarkar 1993, Xu et al, 2019). Data from satellites and self-reported surveys both have independent limitations and biases that may affect overall interpretations. Policy decisions and projected water needs are often configured based on current trends in irrigation. The purpose of this study is to compare irrigation trends through time as reported by different data sources to better inform policy decisions regarding water management practices in agriculture. We aim to further constrain biases and assess resulting interpretations of farming behavior for consistency across data collection methods. We also aim to address limitations in current validation statistics commonly used in remote sensing.

2. Study Area

Our study area is the Kansas portion of the High Plains Aquifer region. The broader HPA underlays portions of 8 states: Colorado, Kansas, Nebraska, New Mexico, Oklahoma, South Dakota, Texas and Wyoming. It covers over 453,000 km^2 of the southern Great Plains, bounded by the Central Lowland to the east and the Rocky Mountains to the west. The aquifer consists of four geologic formations, the largest being the Ogallala formation (Gutentag et al., 1984). The HPA is often split into three regions based hydraulic conductivity and saturated thickness (McMahon et al., 2006; Weeks, 1988); the Northern High Plains (NHP), Central High Plains (CHP), and Southern High Plains (SHP). In Kansas, the NHP and CHP meet. The NHP in Kansas is primarily the Ogallala formation while the CHP in Kansas is composed of the Ogallala in the west and Quaternary fluvial and eolian deposits in central Kansas (Gutentag et al., 1984). Saturated thickness was highest in the southwest corner of Kansas, but this area has seen some of the greatest declines of available groundwater storage in the state through time (Haacker et al., 2016; Weeks, 1988).

Settlement and agricultural development of the region were first impacted by legislation enacted in the 1860s, which made fertile land affordable and encouraged agricultural production and research through land-grant institutions (Gutentag et al., 1984). Since aquifer development with high-capacity wells became widespread in the mid-1960s (R. L. Luckey & Becker, 1999), groundwater has been paramount for irrigation in the High Plains. Although irrigation efficiency has increased through time due to modernization of agricultural irrigation (López-Gunn et al., 2012), the increased demand for irrigated crops paired with climate factors has led to dramatic declines in water storage. If these trends continue, more and more of the aquifer will become unusable in the relatively near future (Cotterman et al., 2018a; Haacker et al., 2016; Smidt et al., 2019). In 2010, 12 million cubic meters of groundwater were withdrawn per day in Kansas alone, the equivalent of about 4,800 Olympic swimming pools per day (Maupin et al., 2014). This massive amount of water is used to irrigate crops, primarily corn, pastureland, sorghum, soybeans, and wheat (NASS, 2017).

The study area contains 37 Kansas counties, including any county with a majority of land overlapping the HPA; eight counties lie within the NHP while the remaining 29 are part of the CHP (Figure 1.1). County-level statistics derived from survey data in the Kansas Water Information Management and Analysis System (WIMAS, Wilson et al., 2005) over the 1996 to 2017 study period show an annual average groundwater use of 104 million cubic meters for irrigation per county. There have been substantial changes in irrigation technologies over the duration of the study period, which affects both water use and irrigated area. Irrigated area according to WIMAS ranges from about 3,076–99,148 hectares per county with an average of ~30,000 hectares. Summaries of GRIDMET gridded climate data for this region (summarized in Google Earth Engine, (Abatzoglou, 2013; Xu et al., 2019)) show county-level average growing season precipitation from 309–550 mm with an average of 392 mm. The growing season in this study is considered May 1st through October 15th of the given water year. Variations in aquifer availability, crop type, and climate variables over the study period in Kansas affect how much land is irrigated for agriculture.

3. Materials and Methods

Most data processing and analyses for this study were performed in R 4.0.2 (R Core Team, 2020) using the *MASS* (Venables & Ripley, 2013) and the *car* (Fox & Weisberg, 2019) packages. ArcGIS 10.5 was also used for mapping and other data processing (Esri Inc., 2020). Prior to analysis, all data was subjected to unit conversions and quality-checks.

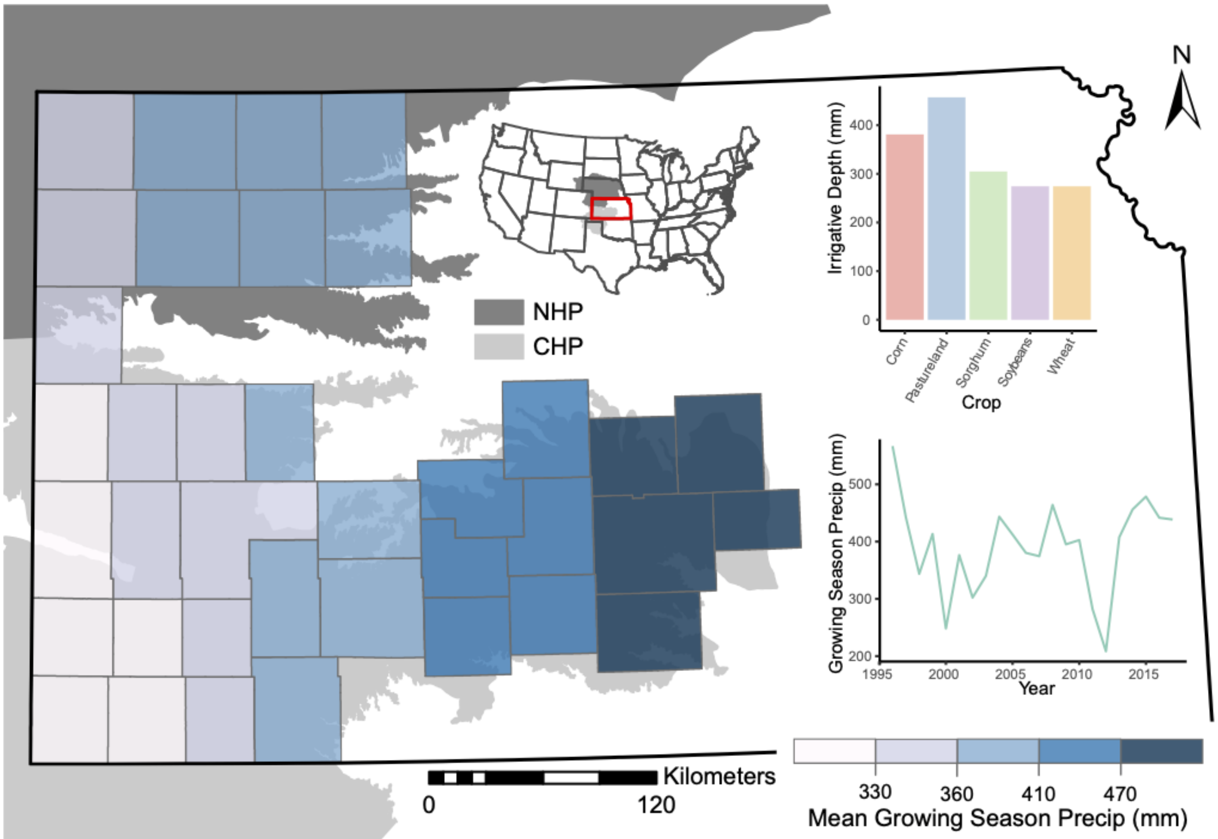

Figure 1.1. Map of the study area in the High Plains Aquifer region of Kansas, US. Northern and Central High Plains regions are dark and light grey, respectively. Counties in the study area of Kansas are colored by average growing season precipitation, and this legend is in the bottom right. The top, right graph shows irrigative depth for the top five most prevalent crops in the state during the study period according to NASS, 2017. The bottom, right graph shows the annual average growing season precipitation across the region through time from 1996 to 2017.

3.1. Data Sources

3.1.1. Survey Data

Survey data from the Kansas WIMAS database were compiled annually during the 1996 to 2017 study period. WIMAS provides farmer-reported statistics relating to agricultural irrigation, and all survey responses are filed by water right and point of diversion (PDIV) identification numbers. The WIMAS features we used were irrigated area and water use for irrigation, although WIMAS includes many other informative fields. All PDIVs (geographic location of the wells or surface water locations where water is diverted to irrigate) were mapped and filtered by both location and diversion type. Only PDIVs that fell within the boundaries of both the HPA and the counties in the study area were included. This was done to best match the spatial coverage of satellite-derived data. PDIVs were then filtered to include only groundwater sources. This filtering was done because irrigation wells sourced from groundwater are strictly metered for water use. Of the small number of surface water diversions that exist in the study area, ~ 98% had incomplete records. A total of 47,380 PDIVs were included in this study, with an average of about 1,200 PDIVs, or wells, per county.

We also used survey data from the Census of Agriculture conducted by the USDA National Agricultural Statistics Service (NASS). NASS data provides county-level data summaries of census responses taken every five years (NASS, 2017). NASS includes many other statistics, but we only used irrigated area by county for this study. To match the time period of the WIMAS data used in this study, only NASS data in and after 1996 were used. Although useful for large-scale trends in irrigation, we were limited by the coarse temporal resolution of NASS for detailed comparisons to other data sources.

Finally, we used irrigated acreage and irrigation water use from groundwater, as compiled by the USGS National Water Use Information Program (USGS, 2016). Water-use information is collected by the USGS in cooperation with local, state, and federal agencies. Water-use data are then summarized by county, state, and national levels every five years. The coarse temporal resolution of USGS limited our ability to compare this data to others in detail. Since the USGS works with the Kansas Geological Survey, WIMAS and USGS data were expected to be very similar. However, small differences may occur due to data cleaning and summarizing techniques. Since the USGS and WIMAS datasets are often utilized as separate sources and are summarized and cleaned using different methods, we include these datasets as separate entities in our comprehensive comparison of irrigation trends.

3.1.2. Satellite-Derived Data

Aside from survey-reported irrigated area, we used remotely-sensed Annual Irrigation Maps (AIM-HPA hereafter AIM; Deines et al., 2019) created by classification of Landsat satellite imagery. In Google Earth Engine, a random forest classifier identified irrigated area at 30 m resolution across the entire High Plains region from 1984 to 2017. AIM was created to encompass the extent of the HPA, and this limited the county and well-data we used for our study. To match the study period set by survey data availability, only AIM irrigated area during and after 1996 was considered. The 30 m irrigated pixels in each county were summed to calculate AIM reported irrigated area to match the county-level spatial resolution set by the most spatially coarse survey data.

3.2. Data Processing

3.2.1. Irrigated Fraction and Irrigative Depth

To standardize how irrigated area was compared across counties, irrigated fraction of counties and rate of irrigated fraction change through time were used in this study. County sizes can vary widely, thus irrigated fraction allows counties to be compared more readily. Rate of irrigated fraction change through time minimizes the effect of the coarse temporal resolution in both USDA and NASS data. Irrigated fraction and change in irrigated fraction statistics are calculated by Eq. 1.1;

$$Irrigated\ Fraction\ (IF) = \frac{Irrigated\ Area\ (m^2)}{County\ Area\ (m^2)} \quad and \quad \frac{\Delta IF}{n} \qquad \text{(Eq. 1.1)}$$

where n is the number of years between the irrigated fraction change. In some cases, irrigated fraction has been converted to percentage for better data visualization.

Another mechanism we used to standardize data sources for direct comparison was irrigative depth, defined as the depth of water applied per unit irrigated area per year. It is calculated using Eq. 1.2 shown below;

$$Irrigative\ Depth\ (ID) = \frac{Water\ Use\ (m^3/year)}{Irrigated\ Area\ (m^2/year)} \qquad \text{(Eq. 1.2)}$$

Irrigative depth is typically converted to millimeters per year. Direct comparisons of this metric minimized the effect of mismatch between county and HPA spatial coverage. In survey derived irrigation rates, irrigative depth was calculated with the available water use for the corresponding years. WIMAS and USGS survey data included groundwater use for irrigation, so irrigative depth was calculated independently for both data sources (though as noted earlier the USGS data bear striking similarity to the WIMAS values). In NASS survey data, the irrigative depth was calculated with NASS irrigated area and water use from annual WIMAS survey data. In satellite derived irrigation rates, remotely sensed irrigated area was also paired with water use from WIMAS survey data.

3.2.2. ANOVA

Robust, one-way and two-way analyses of variance (ANOVAs) were performed to identify differences in irrigated acreage and irrigative water use across data sources. For ANOVA evaluation, it is important to examine the independence, normality, and equal variance between groups. All irrigated fractions met Kolmogorov-Smirnov tests for normality, but the variances across sources were significantly different according to a Bartlett test (Lehmann & Romano, 2006; Marsaglia et al., 2003). We thus utilized robust ANOVAs, which do not assume that the variance is equal amongst groups (Welch, 1951) and account for these differences when assessing for differences in means.

One-way ANOVAs test the variation in group means relative to one independent variable. This method of hypothesis testing provides information to establish differences, or lack thereof, in categorical data (Lehmann & Romano, 2006). For this study, our independent variable was the data source. The dependent, continuous variables in which we hypothesized no difference were irrigated fraction and irrigated water use. Two-way ANOVAs test the variation in group means relative to two independent variables. In our two-way ANOVAs, the data source and the High Plains subregion (NHP or CHP) were the two independent variables. The dependent variables remained the same.

3.2.3. Regression Modeling

Robust linear regression modeling is a form of the traditional linear regression modeling that minimizes the effect from outlying data. Robust linear modeling (RLM) in R was done by iteratively re-weighting the traditional least squares linear model fit (Hampel et al., 2011; Venables & Ripley, 2013). By identifying outliers and assigning ever-decreasing weights then recalculating the least squares fit, RLM optimizes the regression fit relative to extreme data. This method is valid to represent trends in this study because outliers have not been removed from the analysis to preserve completeness of survey data. The slight mismatch in county and HPA spatial coverage also induces error in both AIM and WIMAS data, which may lead to extremes in our relative statistics. Robust linear models identify relationships that would otherwise be difficult to understand due to data extremes.

4. Results and Discussion

Analysis of irrigated fraction and irrigated depth through time indicated that, although individual summary statistics did not show any significant differences, different data types provided inconsistent trends over the last two decades in the High Plains Aquifer region of Kansas. Identifying relationships between irrigation, climatic, and economic variables through robust linear regressions indicated potentially contrasting behavioral patterns reflected by each data type. The traditional method of modeled versus observed correlations for model validation or data comparison does not account for trends over time. This study shows the importance of considering temporal trends and contrasting interpretations when drawing conclusions from data collected via different methods.

4.1. Irrigated Area Trends Through Time

According to robust two-way ANOVAs, the irrigated fraction did not significantly differ by data source when considering the HPA subregion in Kansas (Table 1.1). This was true for all years for which we had overlapping data. This was also true when running the analysis over the entire study period. The lack of significance indicates that within our Kansas subregions, the irrigated fraction reported by different data sources did not have large differences in averages. Since mean is a representative statistic of data with a normal distribution, we concluded that the satellite-derived data reasonably represents the survey data. This conclusion implies that satellite-derived data and survey data provide society with the same information. Robust two-way ANOVAs between water use reported by USGS and WIMAS also showed no significant differences in means across the available samples ($n = 4$), allowing us to draw the same conclusion that water use reported by USGS passably represents WIMAS reported water use.

Year	1997†	2000	2002†	2005	2007†	2010	2012†	2015	2017†	All
Two-way analysis of variance										
p-value	0.956	0.996	0.832	0.999	0.896	0.976	0.914	0.984	0.792	0.758
F statistic	0.0448	0.00352	0.184	$7.06e^{-05}$	0.110	0.0240	0.0898	0.0164	0.235	0.395
One-way analysis of variance										
p-value	0.592	0.995	0.240	0.778	0.480	0.856	0.862	0.907	**0.0356**	**0.0295**
F statistic	0.527	0.00516	1.46	0.252	0.742	0.156	0.150	0.0983	3.50	3.02

Table 1.1. Irrigated fraction significance statistics from one-way and two-way ANOVAs. Table shows values for specific years and the study period as a whole. † denotes years that include WIMAS, AIM, and NASS. In the years when NASS data is unavailable, USGS data is used. Bolded values indicate statistical significance at a 95% confidence level ($p < 0.05$).

Robust one-way ANOVA results generally supported the congruence between survey and satellite data. Even without accounting for subregion, water use reported by the USGS and WIMAS were not significantly different in their means by year or overall. This result is expected as WIMAS and USGS data are very similar because of the similarity in data collection methods. The average irrigated fraction did not significantly differ by data source in any specific overlapping year except 2017. One-way ANOVA also showed a significant difference across all years without incorporating subregion. This significant difference in 2017 could be an error in AIM classification or survey response-bias such as the increase in nonresponse rates of NASS Census of Agriculture since 2002 (NASS, 2017; Reist et al., 2019). A more likely explanation than error in either data source is that the differences could be a residual effect of the different magnitudes of irrigated fraction in the NHP and CHP subregions of Kansas. This is further supported in that this difference did not occur when incorporating subregions into the analysis.

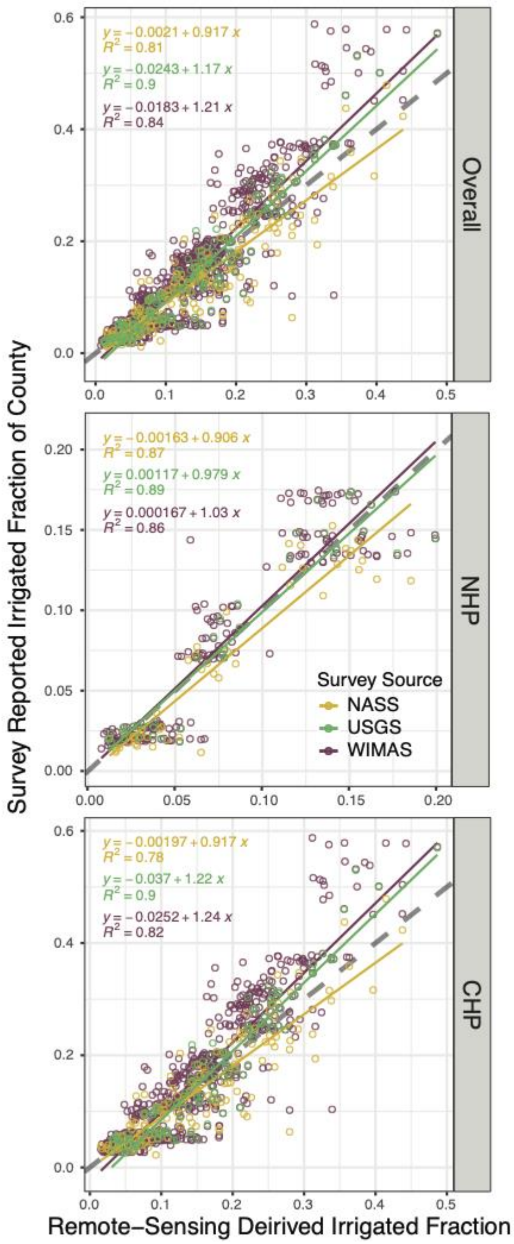

Figure 1.2. County-level comparison of irrigated fraction by aquifer subregion. Survey derived irrigated fraction against remotely sensed irrigated fraction of all 37 counties in the study area for all years in the 1996–2017 study period. Traditional linear regression lines and equations are graphed against a 1:1 (grey dashed) line for reference.

Our conclusion about irrigated area was further supported by the strong correlations and slopes near 1 shown in the linear regressions of Figure 1.2. The slopes near 1 indicated strong congruence of satellite and survey data. Nevertheless, there are consistent differences among datasets. Irrigated fraction reported by WIMAS consistently overestimate when compared to

AIM. In contrast, irrigated fraction reported by NASS is consistently underestimated. Data reported by the USGS typically lies between WIMAS and NASS estimations. These patterns are shown in the linear regression equations reported in Figure 1.2. However, according to the coefficient of determination (R^2) also shown in Figure 1.2, survey data are relatively similar in clustering around the linear regression lines shown by the range of 0.12 in R^2 values.

The frequency distribution of irrigated fraction per county showed strong similarity within survey data sources with some notable differences from satellite-derived data overall (Figure 1.3). The central tendencies in the survey data only differed marginally throughout the study. In any given year, the maximum difference between the median irrigated county fraction between survey sources did not exceed 2.9% in either HPA subregion. However, the difference between survey and satellite data did generally expand through time. In 1997, the first year including two survey data sources, the median irrigated fraction between the two survey data sources averaged 13.3% while satellite median irrigated fraction was 12.6% in the CHP. In the final year of the study period, survey data median averaged 11.3% and satellite data median was 18.1%. The difference increased by nearly an order of magnitude from 0.7% to 6.8% throughout the study.

From year to year, changes occurred within each data source. The median and mean irrigated fraction increased during the study period in the satellite-derived data in both subregions, most visibly in the CHP where the median began at 10.2% and ended at 18.1%. Through time, the satellite-derived data appeared to shift from a normal to a bimodal distribution in the NHP, although the resulting distribution was not significantly non-unimodal ($p = 0.17$). This initial extension made satellite and survey data distributions more similar. As the NHP satellite data distribution shifted toward greater irrigated fractions in later years, it no longer matched survey data. This is seen in the difference in WIMAS and AIM median irrigated fraction in 1996, 2006, and 2016 (1.8%, 0.13%, and -0.95% respectively). Over the last decade of the study period, the average farm size in the United States increased by more than 5% (NASS, 2017). The change from normal to bimodal distributions in the NHP could indicate an increase in large farm irrigation, while maintaining irrigation on the smaller farms thereby increasing the average farm size.

The spread of satellite-derived data stayed relatively constant whilst expanding in the survey data in the CHP (Figure 1.3). This can be seen in the inter-quartile range (IQR) of each data source, which measures the spread of the middle portion of data. In the CHP, the average IQR of survey data sources was 17.1% in 1997 and 13.4% in 2017 while the IQR for the satellite data was 13.8% in 1997 and 12.5% in 2017. In the NHP however, the opposite is seen. The average IQR of survey data sources was 9.68% in 1997 and 9.99% in 2017 while the IQR for the satellite data was 9.18% in 1997 and 10.3% in 2017. The spread and shape of the distributions of survey and satellite data differed only slightly from each other as shown in the statistics above, which is expected based on the ANOVA results. The starkest difference between the two was the lack of movement for irrigated fraction peak frequency (Figure 1.3) in survey data relative to remote sensing data. The range in annual peak irrigated fraction in WIMAS survey and AIM satellite data were 0.72% and 12.7% respectively in the CHP, which is the region with the majority of county data. Only WIMAS was compared here because it is the only survey with annual information. This stable pattern in central tendency is something often seen in survey data because the human psychological preference for consistency affects response behavior (Cialdini, 2006; Falk & Zimmermann, 2013). Survey data tends to be more stable with changes to outward drivers such as climate. This may occur for multiple reasons. Consistency in surveys may be a matter of ease and efficiency for reporters, especially in forms collected online. In this region specifically, allocation of natural resources for consumption is also dependent on use, which may incentivize static reporting at full consumption. To minimize false reporting in Kansas, the Kansas Geological Survey implemented mandatory metered groundwater wells. The farmer-reported survey data in WIMAS also undergoes random, strict on-the-ground verification (Wilson et al., 2005).

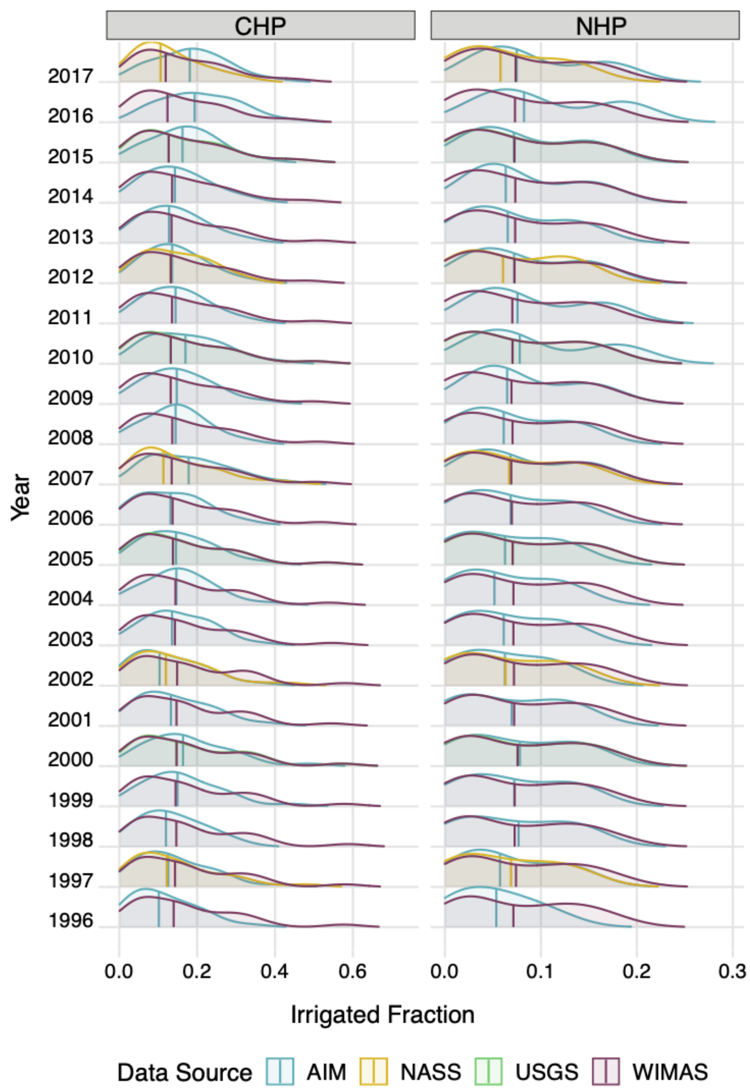

Figure 1.3. Annual frequency distribution of county-level irrigated fraction. Annual distributions are shown for each year in the study period. Distributions are colored according to data source and separated by High Plains Aquifer subregion. The lines mark the median of each distribution.

Robust linear modeling of the annual irrigated proportion of the study area showed significant, inconsistent trends during the two-decade study period (Figure 1.4). Over the whole study area, survey-derived WIMAS data showed a significant trend of -0.5% per decade ($F_{1,20} = 86.8$, $p < 0.001$, RMSE = 0.177), which contrasts with the significant positive trend of 1.6% per decade indicated in satellite-derived AIM data ($F_{1,20} = 9.40$, $p = 0.00609$, RMSE = 1.74). This pattern held true in the CHP subregion. WIMAS data showed a significant trend of -0.7% per decade ($F_{1,20} = 107$, $p < 0.001$, RMSE = 0.177) while in contrast, AIM data showed a significant positive trend of 1.6% ($F_{1,20} = 6.70$, $p = 0.0175$, RMSE = 1.99). The difference in temporal trends in the NHP was not as stark; survey data showed no trend through time (p = NS), which was inconsistent with the significant positive trend of 1.5% per decade ($F_{1,20} = 24.9$, $p < 0.001$, RMSE = 1.12) indicated by satellite data.

Although our data sources were all similar via summary statistics and direct comparisons, our temporal analysis showed that irrigation trends differed by data source. This would suggest that data sources collected by different methods are not as close as traditional validation methods have implied. Contrasting data interpretations such as these may lead to opposing decision-making regarding conservative farming practices. The ANOVA results (Table 1.1) paired with further statistical analyses shown here, may have large implications. Based on trends shown in Figures 1.3 and 1.4, it is possible that the differences identified by ANOVA are indicative of the satellite-derived and survey data trends shifting through time. This shift can be seen in the distribution changes of irrigated area per county, as seen in Figure 1.3 or the summary statistics with opposing linear regressions shown in Figure 1.4. This has two primary implications.

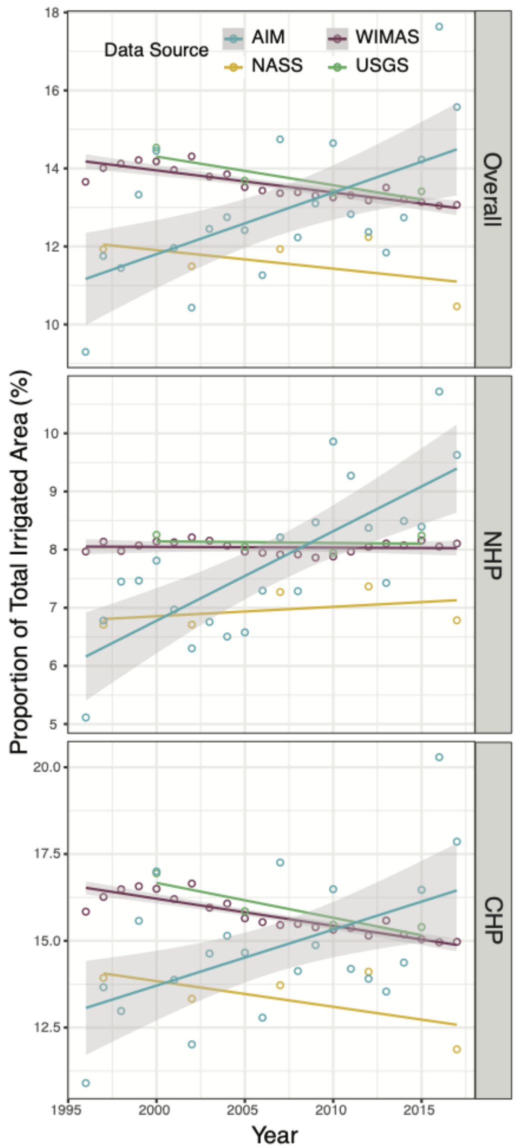

Figure 1.4. Annual irrigated proportion of study area through time in as a percentage. Robust linear regressions are graphed with shaded regions showing 90% and 99% confidence intervals for AIM and WIMAS respectively. Confidence intervals were not added to NASS and USGS data given the limited data availability.

The first implication of different data sources shifting through time is the critique of tradition validation methods. Here, we show modeled versus observed correlation does not account for an important factor, the temporal trends. Forecast modeling has become a foundational tool at the intersection of science and policy (Klein, 1984; Saha et al., 2006). To be an effective tool, there must be certainty in not only numbers but also in temporal trends. It is thus important for both the correlation method and patterns through time to be analyzed in the future when validating and applying models, especially those that involve modeling human behavior. Second, this juxtaposition in irrigated area trends of different data types is important to consider for policy creation and sustainable farming practices moving forward. Decision-making on a state and local level could depend on which data type is publicly available, easily accessible, and widely used.

With severe depletion in HPA groundwater, many tactics have been implemented to extend the lifespan of the aquifer. Many of these solutions focus on water use—adapting more efficient irrigation technologies, managing groundwater withdrawals, or even integrating specific crops and livestock to decrease water use while maintaining or increasing agricultural production (Allen et al., 2007; B R Scanlon et al., 2005; Sophocleous, 2010). In Kansas and around the world, research has shown that an increase in more efficient irrigation technologies results in a possible increase in irrigated area and an overall null effect on the decline of the aquifer (Pfeiffer & Lin, 2014; Sears et al., 2018; F. A. Ward & Pulido-Velazquez, 2008). Based on the trends in survey data, there was no significant increase of irrigated area in the region. This would indicate that to sustain the aquifer, managing the efficiency and extraction of groundwater is key. However, based on the trends shown in AIM, there may be another avenue to sustain the aquifer. Capping water use along with irrigated area would lead to decreases in groundwater withdrawal, provided more efficient irrigation technologies were implemented. Future problems with aquifer sustainability are identified through the available data, and the solutions society investigates depend on the problem. Therefore, it is paramount that we consider all data types with their similarities and differences to make decisions about pathways toward sustainable practices.

4.2. Irrigated Depth Trends

The relative patterns of average county-level irrigative depth were consistent across data sources while the variance within each data source greatly differed over the study area. In central Kansas, the eastern portion of the CHP subregion, most sources showed relatively low irrigation depth (Figure 1.5) ranging from 0.10 to 0.40 m per year. In the western portion of the CHP, most data sources had relatively high irrigated depth ranging from 0.30 up to 0.75 m per year, which is expected based on the large aquifer thickness and volumes of groundwater extraction in this region (Bridget R Scanlon et al., 2012; Weeks, 1988). In the NHP subregion of Kansas, all irrigative depths derived from survey data exhibited little variation, especially in data reported from USGS with all county averages between 0.25 and 0.35 m per year. The satellite-derived irrigated area showed more variation, which coincides with the wider spread in AIM irrigated area. Using remote sensing data, these counties ranged from 0.10 up to 0.45 m per year. The starkest contrast was in the variance differences for each data source. Although USGS and WIMAS had statistically non-significant differences in water use or irrigated area, the variance within and scale of irrigated depth of these two sources was very different in appearance. USGS reported average irrigated depth only varied by up to 0.30 m per year while WIMAS reported average irrigated depth varied up to 0.40 m per year. WIMAS and AIM both utilize the same water use information, but their variation is not equal (up to 0.40 and 0.65 m per year respectively) even though ANOVAs showed non-significant differences in irrigated area (Table 1.1).

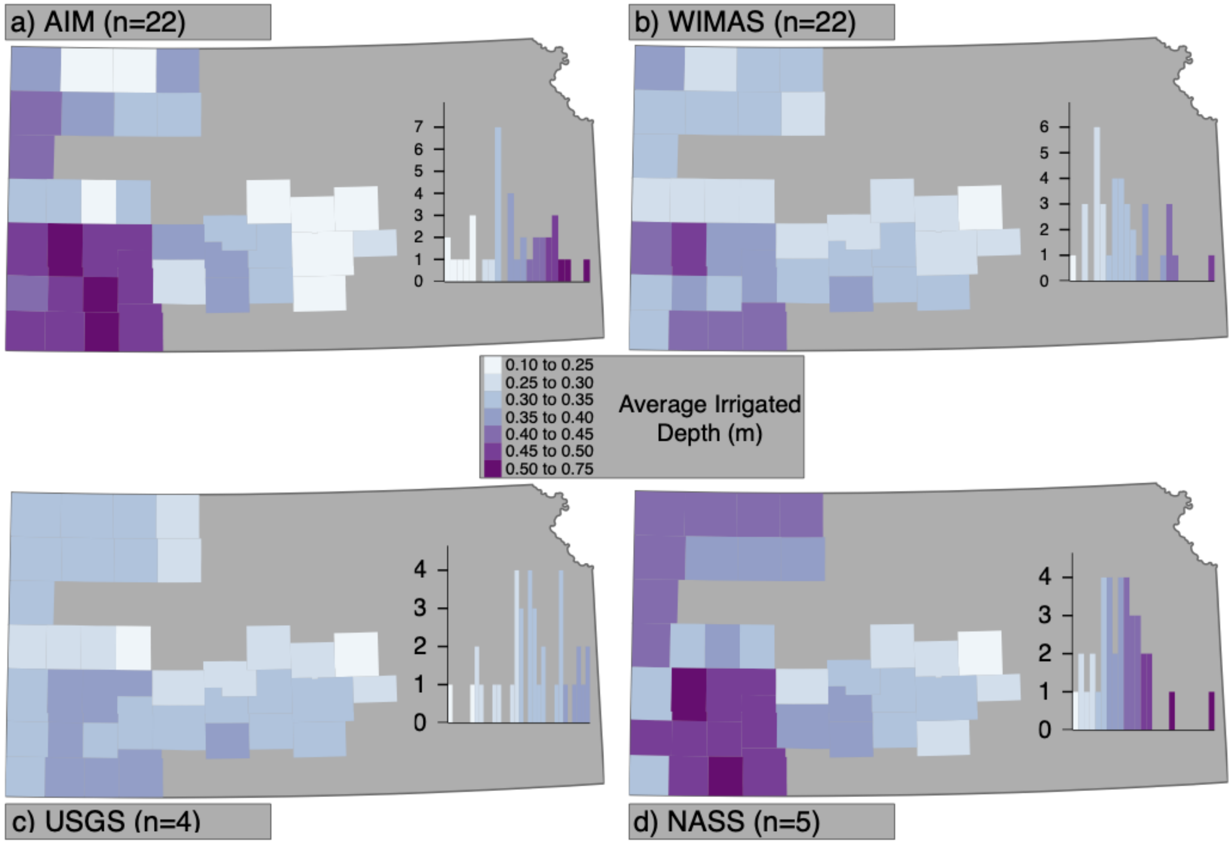

Figure 1.5. Average irrigation depth per county by data source. Irrigation depth for (b) and (c) calculated using survey data within each source. Irrigation depth for (a) and (d) calculated with WIMAS reported water use due to data availability. Histograms show frequency distribution of county values.

The small sample size is one factor that could affect the difference in variance. The five-year span in which USGS and NASS data is collected and aggregated limits the use of the data. Of the five years available of NASS data, two were identified as drought years based on the combination of relative precipitation and the Palmer Drought Severity Index (PDSI, (NOAA, 2017; Palmer, 1965)). PDSI is a comprehensive measurement of drought that accounts for precipitation and temperature. The impacts from the two drought years, 2002 and 2012, likely resulted in the high average irrigated depth exhibited in NASS. The opposite is true in USGS data. Three of the four sample years were relatively yet years, meaning they had more precipitation. This was likely a large contributor to the relatively low irrigated depth exhibited in

USGS data. When the sample size is small and coarse in temporal resolution, not only is the data insufficient for in-depth analyses of trends and patterns through time, but also the conclusions drawn about irrigated area and water use are sensitive to underlying annual drivers such as changes in climate or crop prices. Therefore, the USGS and NASS data were not included in the following analysis.

Irrigative depth within counties through time showed a negative relationship with growing season precipitation in both WIMAS and AIM data (Figure 1.6). The indirect correlation identified overall and across most counties (Figure 1.6a) is the same pattern identified in the NHP Republican River Basin (Deines et al., 2017). The average of all county regression lines for both AIM and WIMAS had negative slopes (Figure 1.6b). Respectively, these slopes were negative 0.33 mm and 0.36 mm of irrigative depth loss per 1 mm of growing season precipitation gain overall. Negative average slopes were also observed when broken into subregions. The AIM slopes were -0.41 and -0.30 in the NHP and CHP respectively. Average WIMAS slopes were also negative. Respectively, they were -0.42 and -0.33 in the NHP and CHP. As precipitation during the growing season increases, it is expected that farmers use less water on their farms. The average negative slopes were not significantly different between the two data sources. This bodes well for the use of future remote-sensing irrigation data, as satellite and survey data share similar interpretations.

Variation in irrigated depth across counties indicates that farming practices vary at the county level. Both data sources convey this however, AIM shows much more county-level variation in overall irrigative depth than WIMAS does (Figure 1.6a). Irrigative depth depends on soil, crop type, and climate. Figure 1.1 shows variation in precipitation across counties, and we expect to see similar variation across irrigative depths. It is possible that the variation of total applied water between counties shown in AIM is a better representation of the differences in water use across the study area. Assessing county-level crop type and soil characteristics is beyond the scope of this paper, but knowing this information would aid in assessing which data source most accurately represents the water needs of Kansas counties.

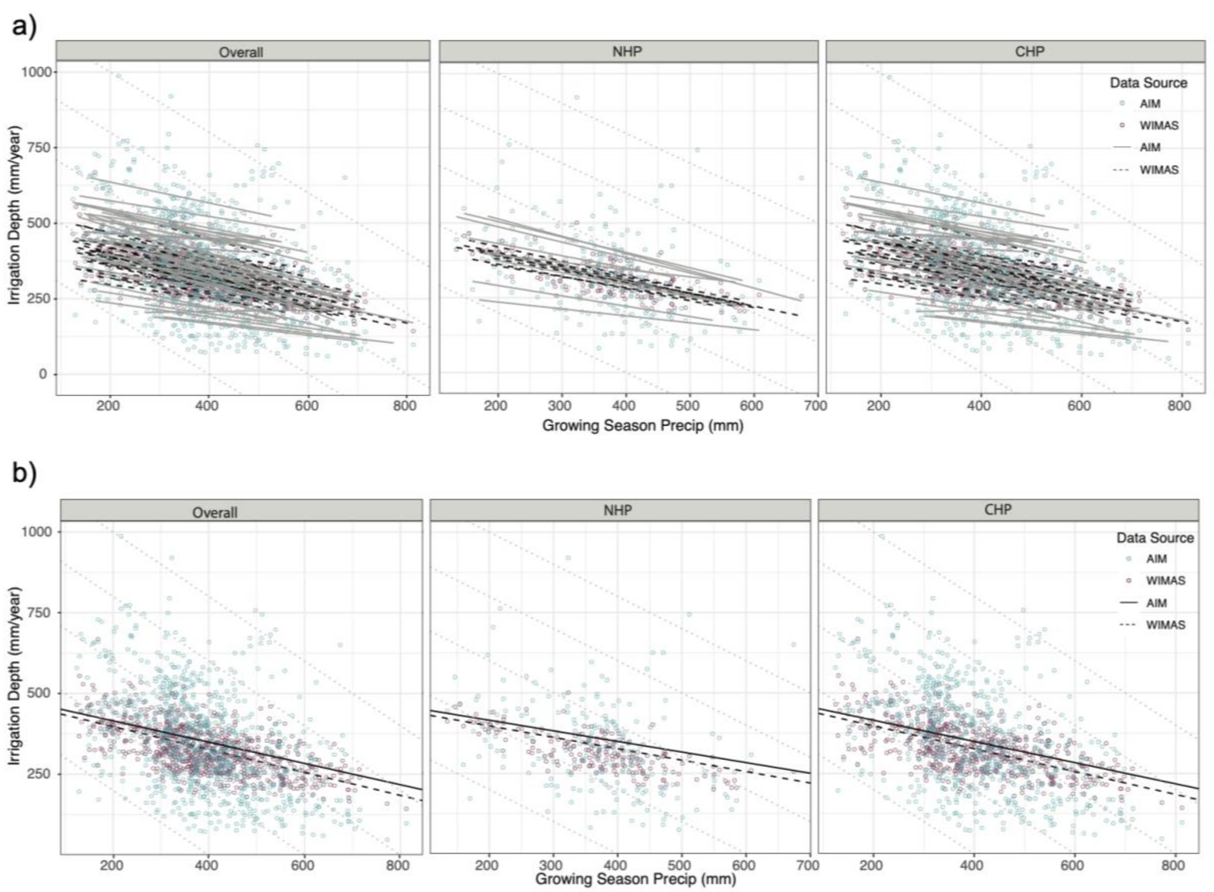

Figure 1.6. Irrigated depth against growing season precipitation. Data points are colored by source. a) Traditional linear regression trendlines drawn for each county, solid lines are AIM data and dashed lines are WIMAS data. b) One countywide average traditional linear regression line for each data source calculated by averaging the slopes and intercepts from (a). Gradient lines (grey dashed) indicate total applied water levels at 200 mm intervals from 400–1200 mm.

Total applied water includes the growing season precipitation plus the depth of irrigation water artificially added to the field (irrigative depth). In Figure 1.6, the dashed grey lines indicate constant levels of total applied water. That is, anywhere on the line representing 400 mm shows a total applied water of 400 mm. We expect that as rainfall increases, farmers will decrease irrigation accordingly. However, a complete direct replacement of rain for irrigation will never be attainable due to variable duration and intensity of rainfall causing overland flow (Horton, 1933). This supports the relationships shown here, as none of the trend lines were steep enough to indicate a direct replacement of rain for irrigation (i.e., neither had a slope of -1). The steepest slope in AIM was -0.67 and the steepest slope in WIMAS data was -0.48. Crop insurance also affects farmer behavior in the substitution of rain for irrigation. Mandated irrigative depths may lead risk-averse farmers to irrigate failed crops, which explains the increased groundwater withdrawals linked to the acquisition of crop insurance (Deryugina & Konar, 2017). Therefore, it is expected that farmers implement a less than optimal change of 1:1 irrigation to precipitation. This is seen in both data sources.

4.3. The Economic Perspective

We performed a robust linear regression of irrigated area against corn prices received by farmers. After cattle and calves, corn has been the highest agricultural commodity ranked by receipts in Kansas over the last five years (NASS, 2017), so this crop has strong ties to the economic prosperity of farmers in the state. Our results showed inconsistent and counterintuitive correlations amongst different data sources although results of this preliminary analysis show that no regressions were statistically significant. Both USGS and WIMAS showed slightly negative to neutral relationships with corn prices by subregion with overall slopes of -0.18% and -0.13% irrigated area per dollar increase respectively. This implies that irrigated area decreases slightly with an increase in the price received by farmers. However, both NASS and AIM irrigated area showed weak, positive correlations with crop prices and overall slopes of +0.33% and +0.24% irrigated area per dollar increase respectively. This would indicate that irrigated area increased with an increase in crop price. The pattern shown here has also been seen in Nebraska

(Deines et al., 2017). The latter correlation is more plausible, as an increasing profit margin would incentivize growing more crops, thus irrigating more area. Although more plausible and intuitive, many factors contribute to the relationships shown here, and this should not be used as a measure of accuracy. This preliminary analysis shows that irrigated area reported by different sources exhibit inconsistent relationships with an economic variable, which often drives agricultural practices. Although these correlations are not significant, and the slopes are relatively small, the implications of these very different trends are notable.

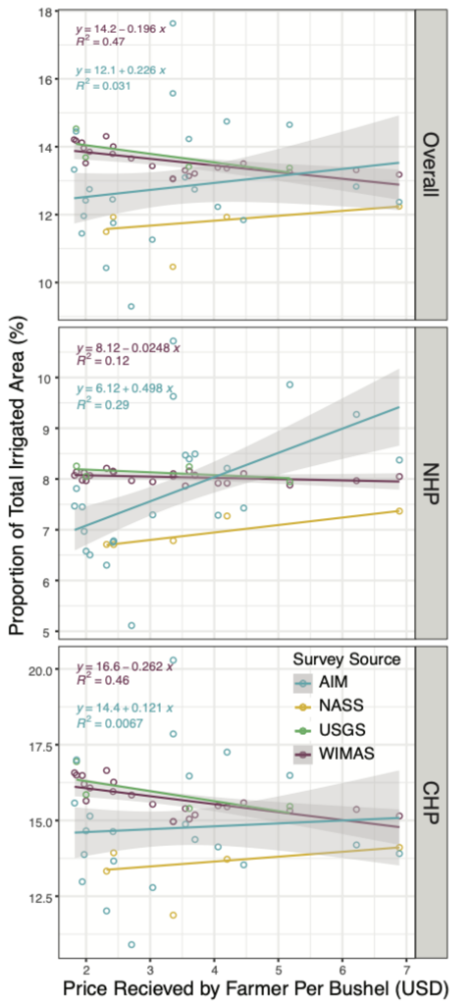

Figure 1.7. Irrigated area of county against farmer profit per corn bushel. Data points and robust linear regressions are colored by data source. Shaded regions on AIM and WIMAS indicate 85% and 95% confidence intervals respectively. Annual corn prices provided by NASS Quick Stats (2017).

5. Conclusions

This study emphasizes the importance of analyzing and interpreting dynamic temporal trends alongside traditional validation methods of summary statistics and static correlations. Comparisons of central tendencies are useful, but they do not fully encapsulate the variation of data distributions overall or through time. Through analyses of variance, robust linear regressions, and normalizations of irrigated area and water use, we show that trends through time may differ even without significant differences in means across datasets. This method of applying basic analyses for data comparison and description should be used to better understand relationships amongst data sources.

Temporal trends through satellite-derived data indicate more variability in irrigated area than survey-derived data, thereby indicating more responsive farmer irrigation practices. The general increase in irrigated area through time demonstrated by satellite data is intuitive because it follows the growth of the population, the growing food need, and the increasing farmer receipts in the United States. Survey data shows strength in consistency and filling in the gaps left by satellite data. Satellite data does not currently have the capacity to collect water use, irrigation methods, and other information that is currently collected in survey data. Irrigated depth identified by both survey and satellite data showed an expected negative correlation with precipitation. As precipitation increases, farmers apply less water to their fields. The wider variation in total applied water represented by AIM indicates a larger difference in farming practices across counties than shown in survey data. The relationship between farmer received price and irrigated area was most intuitive in the data reported by remote sensing, although this does not implicate inherent correctness due to water constraints and other economic incentives. As the economic value of corn increased, the irrigated area by farmers also increased.

Here, we show the contrasting underlying relationships that are captured by different data collection methods. Through a detailed spatial and temporal comparison between datasets, we show that survey data, although consistent and powerful, may not reflect the dynamic nature of farmer behavior and agricultural management practices as well as remotely sensed data does. As farming irrigation practices in the HPA continue to become more driven by the health and overall lifespan of the aquifer, policy will grow in its role of incentivizing and mandating sustainable practices. Policy is often created based on publicly available data. As satellite-derived data becomes more prevalent and widely accessible, it will likely be increasingly incorporated into policy decision-making processes. With supporting survey data acting as additional input, this study shows that remotely sensed data can be an excellent tool to better understand and eventually influence farming practices in the United States and worldwide.

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CHAPTER 2:
IDENTIFYING EFFICIENT IRRIGATION ADOPTION IN THE HIGH PLAINS AQUIFER, US USING STATISTICAL CHANGE POINT DETECTION

Abstract

Irrigation technology exists at the intersection of policy, economy, hydrology, and agriculture. As groundwater withdrawals continue to exceed recharge in agriculturally productive regions, such as the High Plains Aquifer in the United States, aquifer levels continue to decline. In response, innovative irrigation technologies are being implemented to offset groundwater depletion. In the High Plains Aquifer Region, billions of US dollars have been poured into conservation programs to further sustain farming. Although information about agricultural irrigation systems is vital to sustainable management in agriculture, we know little about where, when, and how often irrigation systems are being implemented. Here, we address this unknown by developing a farm-level dataset of efficient sprinkler irrigation adoption in the High Plains Aquifer region from 1990 to 2012. This time window is set by the methods and it covers the period of peak growth adoption in the High Plains region. We applied a change point detection method across the region to identify characteristic changes in irrigation patterns that are likely associated with the adoption of efficient sprinkler irrigation systems. Following the change point detection method, we assessed change points for significance and accuracy in pattern identification. Accuracy as a measure of adoption on the farm-level was 87% in Kansas—the only state where validation data is readily available at this spatial resolution. Irrigation adoption trends were sufficiently identified through this method. Although limitations exist both in the method and in the validation, the application of change point detection to identify irrigation system adoption has great potential as shown in this study.

1. Introduction

Irrigation is likely the most important and prevalent agricultural practice used to meet the growing demands of food production. Globally, irrigation is the primary consumptive user of water, reaching from 80 to 90 percent in arid and semi-arid regions (Döll, 2009; Fereres & Soriano, 2007). Agricultural irrigation also affects climate patterns through increasing precipitation and evapotranspiration (DeAngelis et al., 2010; Pei et al., 2016; Wei et al., 2013) while decreasing temperatures in some downwind regions (Lobell et al., 2009; Thiery et al., 2017). Irrigation effects on climate along with increasing climate extremes due to climate change make for an unstable and unpredictable environment. Although some studies show that moderate climate change could be beneficial for agricultural production (Adams & Hurd, 1999; Howden et al., 2007), irrigation practices will need to adapt to continue food production in a sustainable manner (Nelson et al., 2010). Pumping groundwater for agriculture has been increasingly more difficult due to increasing prices on infrastructure, groundwater depletion, and water pollution (Gutentag et al., 1984; Rosegrant & Cline, 2003). With an increase in water scarcity, irrigation is one of the first sectors to be limited due to its status as the primary consumptive use (Rosegrant et al., 2002).

Irrigation practices affect water loss, recharge rates, and crop yields (Basso et al., 2015; Cotterman et al., 2018a; Holzapfel et al., 1988; Howell, 2003; Warrick & Gardner, 1983). Methods of irrigation also affect energy use and profit (I. D. Carruthers & Clark, 1981; McCarthy et al., 2020). Although many studies have been conducted to further quantify where and when irrigation is happening using remote sensing and national statistics (Biggs et al., 2006; Deines et al., 2017, 2019; Gumma et al., 2011; P. Thenkabail et al., 2009), far less research has been published on irrigation methods. With the exception of mandated self-reporting programs such as in Kansas (Wilson et al., 2005), we have little, public, reliable information of irrigation systems across the globe. In the United States, programs like the Texas Board of Water Development or the nationwide Irrigation and Water Management Survey (USDA NASS, 2017) collect irrigation system information. However, participation is these programs is not mandatory, the nationwide survey only happens every 5 years, and the system information is not readily available on a farm-level.

To better understand interactions across the food-water nexus, integrated agriculture hydrology models have been used to estimate future irrigation demands and effects of aquifer withdrawal on the water cycle (Cotterman et al., 2018b; Foster et al., 2014; Kannan et al., 2011; McNider et al., 2015; Singh et al., 1999; Srinivasan et al., 1998). Models integrating irrigation require assumptions and generalizations about irrigation efficiency and application due to lack of available data (Döll & Siebert, 2002; Droogers & Bastiaanssen, 2002). Depending on the type of irrigation, average field application efficiency, the relation of total water that is stored and used in the root zone relative to the amount of water applied to the field, ranges up to 40 percent (Howell, 2003). Therefore, models may either over or underestimate water needed for irrigation based on their assumed application efficiency and optimized crop water intake. With an overestimation of application efficiency, models have the potential to understate the effects of irrigation on water resources.

Agricultural irrigation adoption and use is also closely tied to economics and policy. Although many climate and hydrologic studies deem sustainable farming practices a necessity for the future, irrigation adoption models predict that farmers will not change to modern, or more efficient, technologies unless the expected investment value largely exceeds immediate costs (Carey & Zilberman, 2002; Seo et al., 2008). To encourage more efficient irrigation adoption, states such as Kansas have implemented water conservation programs based on incentives. From 1998 to 2005, the state of Kansas invested over $5 million USD to support incentive programs such as the Environmental Quality Incentives Program (EQIP, Sears et al. 2018). Programs such as EQIP and other incentive programs through the Farm and Ranch Lands Protection Program (FRPP) can offset the cost of efficient irrigation adoption by up to 75 percent (NRCS, 2004). With the accurate information on irrigation system adoption, incentive-based conservation programs can be better assessed for effectiveness.

Recently, machine learning and convolutional neural networks have been used to identify center pivot irrigation from satellite imagery (Saraiva et al., 2020; Tang et al., 2021; Zhang et al., 2018). This method can feasibly undertake large datasets and perform heavy computational tasks through the training of an algorithm and storing of information in node connections (Feindt & Kerzel, 2006). Due to the dependence on training data, these methods are vulnerable to potential adversarial samples, or input samples that have been modified in an undesirable way leading to incorrect outcomes (Papernot et al., 2016). Neural networks have also been shown to be more texture-biased than shape-biased (Baker et al., 2018; Geirhos et al., 2018), which can be challenging for detecting center pivot irrigation, as it is identified through its distinctive shape (Tang et al., 2021). Although these methods are powerful and have the potential to provide high accuracy, they are typically time and computationally intensive (de Albuquerque et al., 2020; Zhang et al., 2018). Neural networks and machine learning are also only currently applicable on detecting center pivot systems because of the characteristic circular shape. With new technologies and other methods of irrigation being used, this method is currently limited. The method we propose here is simple, has a relatively small computational burden, and is flexible for future modifications and integration with established methods.

In this study, we use a change point detection method to identify efficient sprinkler adoption. Change point detection is the process of identifying rapid variability in time series data. Although originally started in the 50s as a simple signal processing method (E S Page, 1955; Ewan S Page, 1954), change point or break point detection has evolved into a more complex method used in multiple disciplines (Aminikhanghahi & Cook, 2017). In physical sciences, this method has been used to identify changing climate trends, wind patterns, and land degradation (Barr et al., 2013; Burrell et al., 2017; Reeves et al., 2007). Change point detection is an established method to assess remote sensing time series data for variations in seasons and deforestation (Lambert et al., 2013; Verbesselt et al., 2010). To our knowledge, this is the first time change point detection has been used to estimate efficient irrigation adoption.

In this study, we run a change point detection method over farm-level irrigated fraction through time in the High Plains Aquifer (HPA) region. Farmers typically adopt efficient irrigation with the intent of decreasing irrigative water consumption, but with inadequate incentives to understand farm-level water efficiency and a perverse economic incentive to have higher crop yield (Dagnino & Ward, 2012; Koundouri et al., 2006; Levidow et al., 2014), this intended effect is typically diminished or, in extreme cases, reversed (Li & Zhao, 2018; Pfeiffer & Lin, 2014; F. A. Ward & Pulido-Velazquez, 2008; Zwickle et al., 2021). These studies have shown a general increase in mean and median irrigated fraction both on the state level and on the farm level that corresponds to efficient irrigation adoption. Here, we use high resolution, remote sensing irrigated area to gather farm-level irrigation patterns through time across the entire HPA. We use a specified algorithm on continuous irrigated fraction patterns across the HPA to identify characteristic changes that have been linked to efficient irrigation adoption.

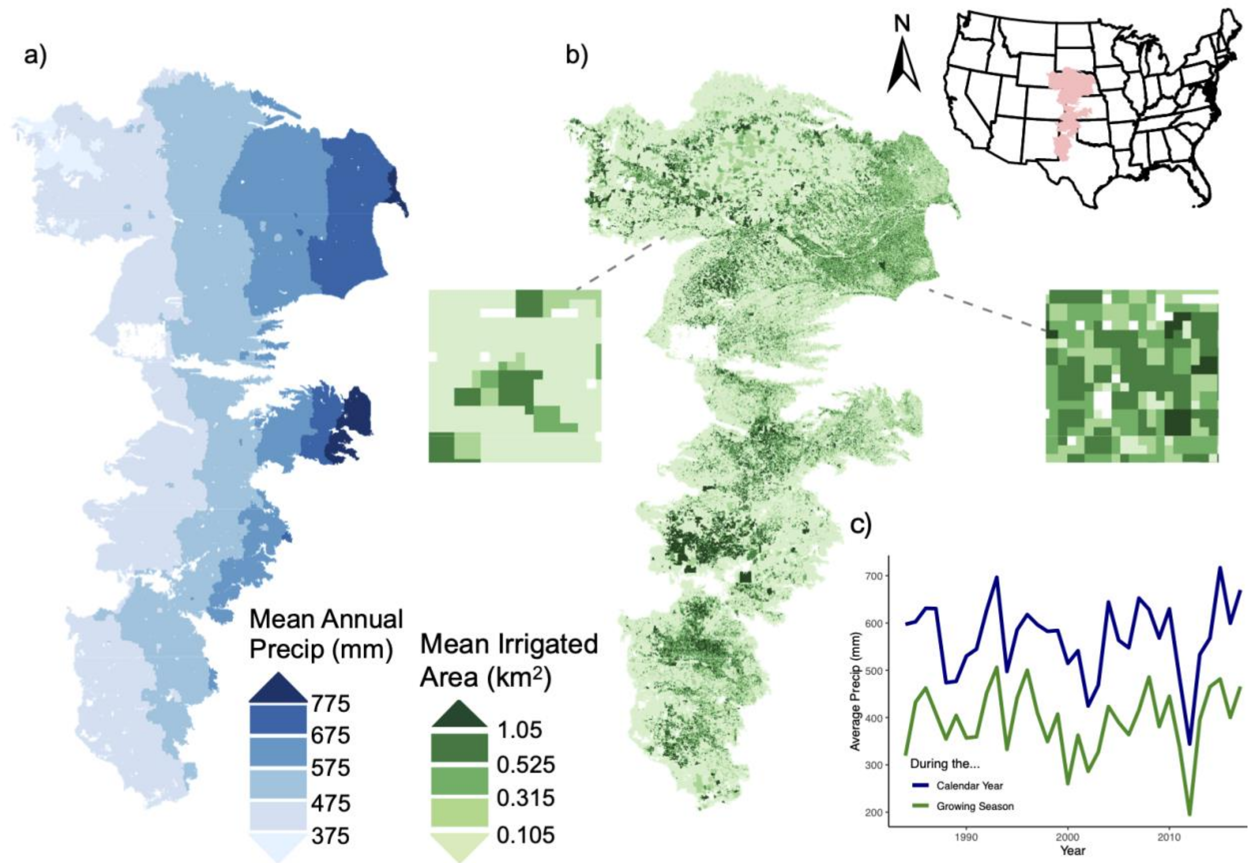

Figure 2.1. High Plains Aquifer study region with United States map for reference. a) Average calendar year precipitation from 1984 to 2017 in mm, as derived from GRIDMET. b) Average irrigated area of farms in the study area during the study period in km^2. Insets show approximate farm values from eastern and western Nebraska at 500 m resolution. c) Average precipitation by growing season and total calendar year over the study period.

2. Materials and Methods

2.1. Background to the High Plains Aquifer

The HPA was the most intensively pumped aquifer in 2000, providing 30 percent of the total groundwater withdrawals for irrigation in the United States (Maupin et al., 2014). This over 450,000 km^2 aquifer, which underlies parts of 8 of the central US states, is paramount for agricultural production in the High Plains region. The aquifer consists of multiple hydraulically connected formations with varying characteristics including the Ogallala, making available water resources and recharge rates inconsistent across the region (McGuire, 2017; Weeks, 1988). The importance of the aquifer to agricultural production varies across the HPA due to differences in water accessibility and availability. As of 2010, groundwater provided 94.7 percent of irrigation water in Kansas but only 13.4 percent in Colorado (Maupin et al., 2014). Although groundwater use differs, overall aquifer declines have been measured throughout the HPA largely due to agriculture (Breña‐Naranjo et al., 2014).

Development of the deep aquifer for agriculture started in Texas in the 1930s and grew northward, leaving most of the aquifer developed by the 1950s (R. R. Luckey et al., 1981; Whittemore et al., 2018). With an increase in aquifer development and the prevalence of high-capacity wells, aquifer withdrawals exceeded recharge rates, resulting in significant aquifer declines across much of the region (R. L. Luckey & Becker, 1999; McGuire, 2012). As the need for agricultural production grows with an increasing population, irrigation has and is projected to increase in the HPA and other regions of the United States (Smidt et al., 2019). The aquifer continues to decline, and if trends stay the same, this could lead to unusable portions of the aquifer for agriculture in the future (Haacker et al., 2016).

The High Plains has abundant sunshine and frequent winds with a mid-latitude, humid continental climate (Dennehy et al., 2002). The mix of climate characteristics leads to extreme weather patterns that are projected to increase in severity and frequency with projected climate change (Dennehy et al., 2002; Pryor et al., 2014). Extreme weather patterns are paired with a distinct south to north increasing temperature gradient and a west to east increasing precipitation gradient, and the variation necessitates different amounts of agricultural irrigation (Figure 2.1). The average annual precipitation during the study period ranges from around 300 mm in the northwest to over 800 mm in the east, and the average temperature ranges from around 45 degrees to over 70 degrees Fahrenheit from north to south (Pryor et al., 2014). The top five most irrigated crops during the study period across the High Plains were corn, soybeans, cotton, wheat, alfalfa/hay, and sorghum, with cotton grown more commonly in the south and soybeans more commonly in the northeast (Deines et al., 2019; USDA NASS, 2017). Here, our study area encompasses most of the High Plains Aquifer region, and our study period is 1990 to 2012; both are modified from Deines et al., 2019. Although our dataset spans from 1984 to 2017, restrictions in our method limit the period in which we predict adoption. The study area is limited to all irrigated area within Common Land Units, and the study period is limited due to the minimum segment size determined in our change point detection.

2.2. Data and Processing

We cleaned, processed, and analyzed data in Python (Python Software Foundation, 2020) and R 4.0.2 (R Core Team, 2020) programming languages. We compiled and cleaned AIM data and identified breakpoints in Python using the *pandas* (McKinney, 2010) and *ruptures* (Truong et al., 2018) packages, respectively. Data analysis and visualization was performed using the *tmap* package in R (Tennekes, 2018) and in ArcGIS 10.5 (Esri Inc., 2020). After extensive cleaning and quality assurance, the data underwent break point detection of irrigated fraction patterns. Finally, we assessed the predicted efficient irrigation adoption years (break points) for significance and for validation relative to available survey data.

2.2.1. Satellite-Derived Irrigation Dataset

We used Annual Irrigation Maps (AIM-HPA, hereafter AIM; Deines et al., 2019) to measure continuous irrigated area across the High Plains region from 1984 to 2017. These remotely sensed maps were created in Google Earth Engine using a random-forest classification of Landsat satellite imagery along with crop and climate data (Deines et al., 2019). AIM provides

30 m resolution pixels of irrigated and non-irrigated area throughout the study area during the study period. The maps are considered of ample accuracy by year, and they are considered to be a sufficient representation of shifting farming practices through time in response to external factors (see Chapter 1 of this thesis; Deines et al., 2017, 2019).

Farm size was determined as the total area of a Common Land Unit (CLU). CLUs are identified as the smallest unit of land with a contiguous boundary and the same landowner (Farm Service Agency, 2012). Each CLU has a tract, farm, county, and state code that makes it unique across the study region (USDA, 2004). We used CLU data from 2016, and all map figures showing these farms have been rasterized at 500 m resolution to preserve the privacy of farms in the CLU dataset. Although we calculated all statistics on the farm level, all spatial visualizations in this manuscript are approximations. This version of the CLU data excludes Kit Carson County in Colorado, thus that region has been omitted from this study. In the HPA, we identified over 380,000 CLUs in total. Of those, 27.1 percent never had recorded irrigation and were thus omitted from this study. Large-scale agriculture irrigation systems focused on in this study have a range sizes, generally above five acres (Evans, 2001). As 13.1 percent of total CLUs did not irrigate more than five acres, they were also removed from the study, leaving ~228,000 CLUs. All CLUs that irrigated above five acres were included in the total farm count and total irrigated area, but not all CLUs with large-scale irrigation underwent change point detection.

Assumptions about efficient irrigation technology adoption further restricted the CLUs that underwent change point detection. CLUs that continuously irrigated below 60 acres and above 640 acres were removed from the study. The thresholds were set due to assumptions about irrigation methods and farm size, and similar assumptions have been made in prior studies that quantified irrigated area change in response to a change in irrigation method (Hendricks &

Peterson, 2012; Pfeiffer & Lin, 2014). Restricting the irrigated acreage in our study reduced the number of CLUs that underwent change point detection to 137,985. The irrigated fraction statistic we used in the change point detection method was the total irrigated area within the CLU as defined by AIM (Deines et al., 2019) divided by the farm size. We used irrigated fraction instead of irrigated area to compare irrigation patterns regardless of the size of the CLU, hereafter referred to as farm. Using irrigated fraction allowed us to compare trends before and after predicted adoption across farms and across states regardless of the size of the unit of area.

2.2.2. Validation Datasets

We used two data sources at different spatial scales to validate efficient irrigation adoption throughout the study area. In this study, efficient sprinkler irrigation is defined as a modified center pivot sprinkler system that requires less than 30 psi to operate. These systems include mid-elevation spray application (MESA), low-elevation spray application (LESA), low-pressure in canopy (LPIC), and low-energy precision application (LEPA; New & Fipps, 2000; Peters et al., 2016). In validation datasets, these systems are either labeled as center pivots with drop nozzles or classified by the psi requirement (Lanning-Rush, 2016; USDA NASS, 2017).

On the state level, validation data were gathered from the Irrigation and Water Management Survey, formerly called the Farm and Ranch Irrigation Survey (USDA NASS, 2017). This survey collects irrigation characteristics every five years, and summary data statistics on water application methods have been released every five years, starting in 2003 (NASS, 2017). The survey is performed in conjunction with the Census of Agriculture performed by the United States Department of Agriculture and is thus representative of the prior year's irrigation information. As a follow-on to the Census of Agriculture, it gathers nationwide information on irrigation and water use practices (USDA NASS, 2017). The survey provides the total number of irrigated farms and notes those using efficient sprinkler irrigation in each state. It also provides the total irrigated area and the area irrigated by efficient center pivot technology. To compare validation numbers to change point detection results, we used two relative statistics: 1) the percent of farms with efficient sprinkler irrigation relative to total irrigated farms within each dataset, and 2) the percent area irrigated by efficient sprinkler irrigation relative to the total irrigated area in each dataset. The latter is a stronger method of validation, as our definition of farm likely does not match a farm unit as defined by the Irrigation and Water Management survey. The average farm size in this study is generally smaller even though total irrigated area is about the same when compared to reported numbers, supporting this assumption. The average farm size, according to the Census of Agriculture, is around 440 acres while the average farm size in our study is 289 acres. To address the limitation that farms may not be equal units in our dataset compared to validation data, we focused our comparison on irrigated acreage. The Agricultural Census survey records how many acres were irrigated by each irrigation method as well as total irrigated acreage of the state.

Our study area is limited to the extent of the HPA, which does not fully encompass any state. The significant majority of withdrawals for agricultural irrigation are sourced by groundwater for half of the states within the HPA region (Maupin et al., 2014); namely Kansas, Nebraska, Oklahoma, and Texas. We assume state-level farm numbers as reported by the USDA lie mostly within our study region in these states. However, we do recognize that this is not the case in all states. Our study area may not be a representative sample of total state-level irrigation practices in other states that primarily use surface water for irrigation and have most of their irrigated area outside of the study region. This is a limitation between our study and the validation data. Using relative statistics instead of raw numbers helps address this limitation by making the data more robust and less sensitive to statewide area coverage. Using percentages also addresses the limitation of using CLUs as our farms here. The farms as identified in the Census of Agriculture may not have the same size or density as the farms we define in this study, and percentages are more robust to these differences.

At a higher spatial resolution, we used well-level data to validate our irrigation numbers. In Kansas, annual irrigation characteristics are self-reported by farmers to the Water Information Management & Analysis System (WIMAS), maintained by the Kansas Department of Agriculture-Division of Water Resources (Wilson et al., 2005). Amongst other information, these surveys collect irrigation methods and irrigated area by point of diversion, or well, and water right owner. Survey reported well data from WIMAS were aggregated to farm levels in a multi-step cleaning process. This process added uncertainty to the validation data by reducing the number of wells and the number of farms with available irrigation information. To address this limitation, we also include a statewide analysis using all WIMAS wells in the study area compared to all CLU farms in the study area (Figure 2.5).

All WIMAS files from 1996 to 2017 were read into Python and cleaned by addressing missing values. After we cleaned point-level data, we aggregated them into farms by location. In the WIMAS dataset, every irrigation pumping well has associated geographic coordinates. We mapped well locations and farms, and we then spatially joined the two in ArcGIS Pro (Esri Inc., 2020). By doing so, wells were tagged with a unique farm identification number, which allowed a portion of the WIMAS data to be linked to AIM remotely sensed irrigation data. Each farm contained 1 to 15 irrigation wells, with a mean of 1.8 wells within each farm. Wells are defined as points of water diversion in this study. Although farms may have multiple points of diversion, it is probable that not all water diverted is being applied to the farm in which the well resides. This is a source uncertainty for our validation data.

The irrigation system of each farm was determined by the contained well(s). If a farm contained more than one well, we used the reported mode (most frequent occurrence) of irrigation systems. According to the Common Land Unit Handbook (USDA, 2004), all farms within the same tract number are under the same ownership and operation, which supports this method of assigning irrigation systems. A limitation of this study is the loss of accuracy by aggregating well-level irrigation systems to the farm-level. To minimize loss of accuracy through aggregation on the farm level in Kansas, we omitted validation farms with counterintuitive transitions and without any recorded adoption of efficient irrigation sprinkler technology (LEPA, LESA, LPIC, and MESA). This intensive filtering was not done on the state-level validation comparison in Kansas, as aggregation was not necessary. The aggregated validation data was only used to assess how close the prediction adoption year was to the actual year, and it was only necessary in Kansas because of the available WIMAS data. For statewide patterns, aggregation was not necessary, thus all WIMAS data were used.

All validation data in this study is by self-reported survey data. Survey data has been shown to have inherent limitations (Falk & Zimmermann, 2013; Groves, 1987; Lesser & Kalsbeek, 1999). The Irrigation and Water Management Survey is encouraged, but not mandatory for irrigators across the nation (USDA NASS, 2017). This estimate-based sample survey has the potential for sampling and non-sampling errors. Sampling error occurs when the sample is not representative of the entire population (Assael & Keon, 1982). Non-sampling error is all error outside of sampling error including failure to respond or responding with misinformation (Assael & Keon, 1982; Lesser & Kalsbeek, 1999). The latter error is considered to be of higher bias (Lessler & Kalsbeek, 1992). Although the WIMAS survey is mandatory for all water rights' holders (Wilson et al., 2005), non-sampling bias is still subject to occur. Using survey data as means of validation further signifies the importance of a non-bias, spatially and temporally ubiquitous dataset of irrigation adoption.

2.3. Change Point Analysis

Change point detection is the process of identifying rapid variations in continuous model signals or time series data. Rudimentary change point analysis was established in the 1950s and has since become widely used for signal processing in other disciplines (Brodsky & Darkhovsky, 2013; Lai, 1995; Ewan S Page, 1954). This approach has been used on research topics from quantifying social network traffic (Ordun et al., 2020) to assessing climatological and land degradation variations (Burrell et al., 2017; Reeves et al., 2007; Verbesselt et al., 2010). In this study, we use a change point detection algorithm on continuous irrigated fraction patterns across the HPA to identify characteristic changes that have been linked to efficient irrigation adoption (Li & Zhao, 2018; Pfeiffer & Lin, 2014; Zwickle et al., 2021).

We applied change point detection to the time series of annual irrigated fraction across selected farms in the HPA from 1984 to 2017 to identify efficient sprinkler irrigation adoption. We trialed multiple change point detection methods, and the results were assessed for the highest agreement with available validation data. Change points, or break points, can be identified by evaluating the change in different statistical variables before and after the break such as a difference in mean, variance, or linear regression (Tartakovsky et al., 2014). Based on the relationships shown in Zwickle et al., 2021, the mean of irrigated fraction and linear regression through time show statistically significant changes after LEPA adoption, and the variance shows a visual change. Here, we identified break points using the following methods; the R function segreg from *segmented* package (Muggeo, 2003, 2008) to identify break points based on changes in linear regression, the R package *causalimpact* (Brodersen et al., 2015) run inversely to check for the year with the largest significant impact, and the Python package *ruptures* (Truong et al., 2018) to find break points based on the kernelized mean change and variance change. Due to data availability, change point detection methods were tested and validated on Kansas farms where we had farm-level information about irrigation systems.

The optimized change point detection method we used here was from the Python package *ruptures*. In *ruptures*, which contains many break point search methods, we used binary segmentation (Scott & Knott, 1974) because it is commonly used, and has a relatively low computational cost (Killick et al., 2012). Binary segmentation is an approximate, top-down detection method (Killick et al., 2012; Truong et al., 2020). In essence, this method minimizes the cost function by identifying one change point over the time series; it then iteratively repeats the search, adding more change points until it has minimized the sum of cost functions or identified the assigned number of change points. Binary segmentation tests the whole time series $y_{1:n} = (y_1, ..., y_n)$ to satisfy the following equation

$$C(y_{1:\tau}) + C\big(y_{(1+\tau):n}\big) + \beta < C(y_{1:n}) \qquad \text{(Eq. 2.1)}$$

where C is the specified cost function, τ is the position of the break point, and β is a penalty to prevent overfitting. If Eq. 2.1 is false, no break point is identified, and the method stops. We limited the search to a single break point, and we did not use a penalty function.

We used kernelized mean change as our specified cost function from the *ruptures* package because it has the flexibility of non-parametric modeling, is easy to train, and has wide applications (Harchaoui & Cappé, 2007; Truong et al., 2020). In this cost function, the time series *y* is mapped with the function $\phi: R^d \rightarrow H$ with an associated semi-definite positive kernel

$k(\cdot,\cdot): R^d \times R^d \rightarrow R$, where H denotes a proper Hilbert space (a vector space with an inner product (Truong et al., 2020; Young, 1988)). The radial basis kernel function is $k(x, y) = exp\ (-\gamma\|x - y\|^2)$ where $\|\cdot\|$ is the Euclidean norm and positive γ is the kernel radius indirectly determined by the median of all pairwise distances. The cost function, simplified by the kernel trick (Celisse et al., 2018), for a segment of time series *y* is

$$C(y_{a\ldots b}) = \sum_{t=a+1}^{b} k(y_t, y_t) - \frac{1}{b-a} \sum_{s,t=a+1}^{b} k(y_s, y_t) \quad \text{(Eq. 2.2)}$$

Given the kernel and associated feature map, this cost function assesses the embedded signal for a change in mean. The *ruptures* package identifies break points where the sum of two cost functions (Eq. 2.2) is lower than the cost over the whole time series. We restricted the minimum segment size to 5 years to prune false change points forced at the beginning and end of the time series, which limited our break point detection to 1990–2012 even though the range of our time series data was longer (1984–2017). The results from the break point analysis provided one most likely break year and two segmented time series for all farms in the study area.

Although vital to identifying where break points exist, the detection method did not provide statistical significance of selected change points. To quantify the significance of the change in mean across the two segments, we used one-sided t-tests. Efforts were made to use more complex, non-parametric measures of significance. The results were similar to the t-tests; thus we chose the simplified method. We used t-testing to measure significance as opposed to other significance methods commonly used, such as the Chow test (Chow, 1960), because t-tests best complimented the cost function (relying on the change in mean). To limit false positive change point detection years from fallowed or abandoned farms, we tested for an increase in mean. Only farms with change points holding an 85 percent confidence ($p \leq 0.15$) were analyzed in this study to regulate the change point detection method. A threshold of 85 percent confidence was used because an analysis of correctly identified change points indicated that not all increases in mean met the traditional 95 percent confidence interval. Setting the interval at 85 percent allows for inclusion of probable break points whilst still providing a relatively strong confidence. Increase in irrigated area has been linked to efficient irrigation adoption (Loch & Adamson, 2015; Pfeiffer & Lin, 2014; Smidt et al., 2019). Farms with change points below this threshold were considered to have no break point detected.

3. Results

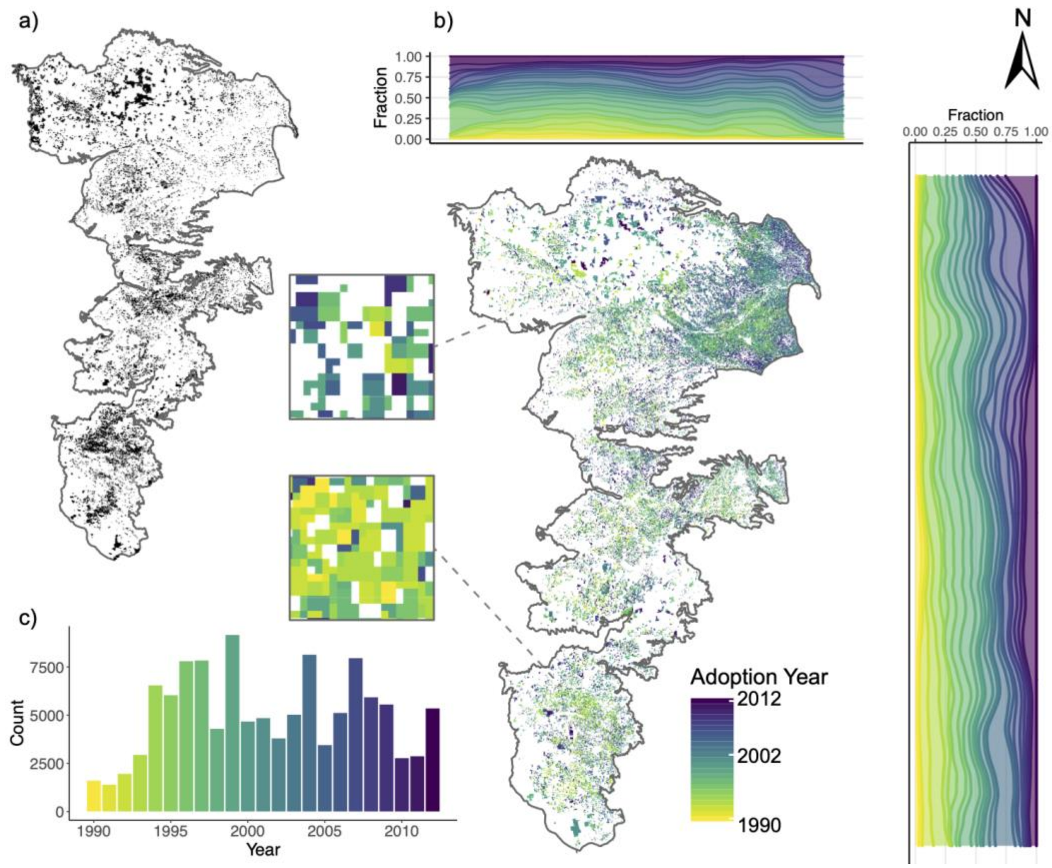

Figure 2.2. Approximation of farm adoption years mapped across the High Plains Aquifer at 500 m. a) Approximation of farms with no significant change point detected. b) Farms colored by year of efficient sprinkler irrigation adoption identified by change point detection with associated, proportioned marginal distributions according to longitude and latitude. Distributions indicate relative patterns from west to east and north to south, respectively. Insets indicate late, spaced-out adoption in Nebraska (top) and early, dense adoption in Texas (bottom). c) Total adoption years through time colored with the same legend used in (b).

In total, 16.7 percent of the farms that underwent change point detection had no breakpoint identified based on the significance filter. These farms with no change point identified either showed decreasing means or did not meet the threshold for significance (Figure 2.2a). Of these, 4.9 percent of farms were likely fallowed, abandoned, or filled with non-irrigation crops based on a near-zero fraction of irrigation after the break point. Most change points detected were filtered because they measure a decrease in irrigated area (81.0 percent of the farms with no breakpoint), and this relationship is rare in efficient irrigation adoption as previously stated. The remaining 18.9 percent of farms had an increase in mean that did not meet the confidence threshold. Farms with no identified change point are most common relative to state farm counts in New Mexico, Wyoming, and Texas (Figure 2.2a).

Figure 2.2 shows the efficient sprinkler irrigation adoption year by approximate farm location in the High Plains Aquifer region from 1990 to 2012 as measured using the change point detection method described above. A total of 83.3 percent of selected farms showed a change point meeting the previously stated thresholds. Early adoption, predicted adoption prior to 2002, is more common in the south than it is in the north (Figure 2.2b). Early adoption also occurs in locations with larger changes in the water table such as the southern High Plains and the middle of the central High Plains (McGuire, 2017; Bridget R Scanlon et al., 2012). Marginal distributions show years with relatively high adoption as thicker ribbons. In the south, 2004 is a year with relatively high adoption. In the north, 2007 and 2008 are years with relatively high adoption. From west to east, there is a slight decrease in early adoption. In the west, 1996 is a year with relatively high adoption whilst in the east, 2007 and 2008 are again years with relatively high adoption. This is likely because the furthest east and north portion of the HPA is in Nebraska, where adoption is predicted to happen later. As shown in Figure 2.2c, adoption of efficient technologies is slightly cyclic. Qualitatively, these cycles match well with drought years and, in some cases, policy changes. There is a large peak of adoption in the last year allowed by break point detection, 2012. Although it is likely that there is more adoption due to drought conditions, the peak in 2012 may also be exaggerated due to the chosen method. Change point detection is sensitive to changes in the beginning and end of time series data.

4. Discussion

4.1. Agreement with Validation Data

Our change point detection method and subsequent filtering for significance produced almost 114,000 farms with an associated year of efficient sprinkler irrigation adoption from 1990–2012 across the entire High Plains Aquifer region. This method appears to have qualitatively captured irrigation adoption trends from south to north, as Texas is thought to have adopted efficient irrigation relatively early due to more extreme water constraints and early statewide conservation incentive programs (Fipps & New, 1990; Seo et al., 2008). The resulting dataset provides adoption years at a much higher spatial resolution than most nationwide and statewide programs that tend to report irrigation method statistics at the state or county level. Models used to predict irrigation adoption typically focus on how crop price, energy cost, or climate and land characteristics affect adoption patterns (Alcon et al., 2011; Caswell & Zilberman, 1986; Cortignani & Severini, 2009; Feder & Umali, 1993). Although valuable, these models do not produce spatially and temporally explicit, farm-level adoption of irrigation technologies, rather they provide overall trends and predictors of adoption. This study, in conjunction with other mathematical models has the potential to confidently predict efficient irrigation adoption globally.

4.1.1. Kansas Farm-Level Validation

In Kansas, farmers are mandated to report their annual water use via statewide surveys, and the data is freely and publicly available from the WIMAS online database (https://hercules.kgs.ku.edu/geohydro/wimas/). Well-level data was aggregated to the farm level for validation in terms of when efficient irrigation was adopted. Although efforts were made to minimize the error introduced during this aggregation, it is important to note that the irrigation system validation information used here is our best approximation of the implemented system derived from Kansas WIMAS. The WIMAS dataset does have strict ground validation (Wilson et al., 2005), but aggregating systems across farms in the way we have here adds uncertainty to the validation data. Another form of uncertainty is in the WIMAS data itself. Although points of diversion are located within a farm, water may be diverted outside the farm to irrigate other areas. It is also important to note that although system information is mandatory, ensuring that all records are complete is a time and resource intensive task.

		AIM Farms			
	n = 97,955	No large-scale irrigation	Irrigation with adoption	Irrigation without adoption	Total
WIMAS Farms	No wells	67,019	15,448	3,485	85,952
	With wells and adoption	905	6,714	544	8,163
	With wells, no adoption	555	813	2,472	3,840
	Total	68,479	22,975	6,501	

Table 2.1. Confusion matrix of farm accuracy in Kansas. Respective number of farms with validation data and change point detection data in Kansas HPA. Total, there are 97,955 farms in Kansas. 29,476 are irrigated on a large scale according to AIM and underwent change point analysis. The gray shaded regions are not included in the omission, commission, and accuracy statistics because they do not measure the accuracy of our change point detection, rather they measure irrigation captured by AIM and filtering.

These factors add uncertainty to our validation data. To address this limitation, statewide irrigation statistics from all wells in the study area were compared to all farms in the study area using summary values (Figure 2.5). In this study, we identified over 29,000 large-scale irrigated farms in Kansas. Of these, 22,975 farms had a significant change point detected (Figure 2.3). Only half of farms in Kansas with identified change points had validation data from WIMAS (Table 2.1) due to well locations being outside the farm areas as defined in this study. This mismatch may also be attributed to our definition of farm as a CLU in this study. The differences between the change point detected adoption year and the actual adoption year in farms with validation data can be found in Figure 2.4.

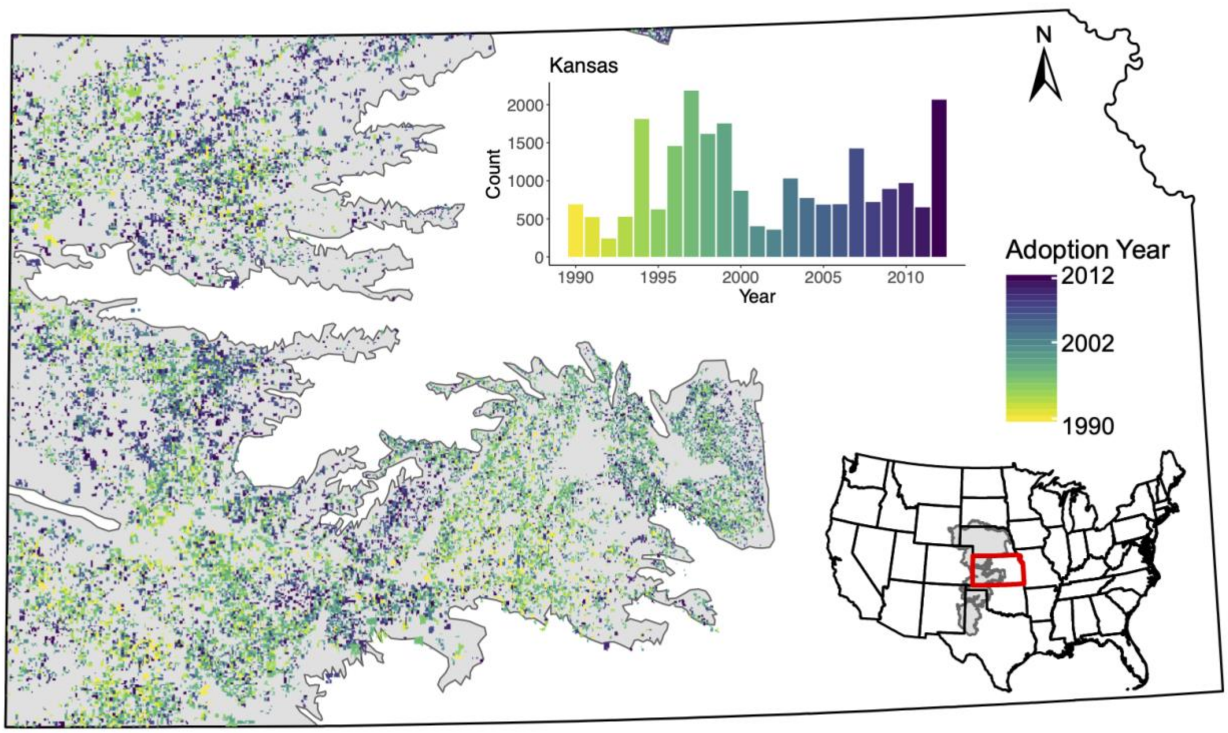

Figure 2.3. Estimated year of adoption of efficient irrigation technologies by approximate farm. Adoption years shown are identified by our change point detection method. Actual farm polygons coarsened to 500 meter resolution for privacy. Adoption years shown with associated legend and histogram of adoption through time in Kansas specifically.

In farms that had both a predicted adoption year and an observed adoption year, the average difference between the two was -2.57 years and the median was -2 years (Figure 2.4). This means that, on average, the change point approach predicted adoption about two and a half years early in farms where we had validation data. Kansas validation data used in this study does not start until 1996 even though LEPA/LESA/LPIC/MESA adoption started in the late 1980s and early 1990s (L. L. New, 1986; Seo et al., 2008). This means that the WIMAS validation data likely does not indicate the first adoption of efficient sprinkler irrigation technology for all farmers. Of the farms with identified change points that also had reported adoption through WIMAS, agreement of adoption year +/- 1 year was 25.2 percent. With window of +/- 2 years, agreement increases to 36.3 percent. We had an omission error of 7.5 percent, meaning that out of every 100 farms with reported irrigation adoption, we identified no change point in about 7.5 of them. This indicates that irrigation adoption could not be detected with irrigation patterns alone in this portion of farms. We had a commission error of 10.8 percent, thus about one tenth of the total farms with identified adoption years had no reported efficient irrigation adoption. Omission and commission errors calculated using Table 2.1 above.

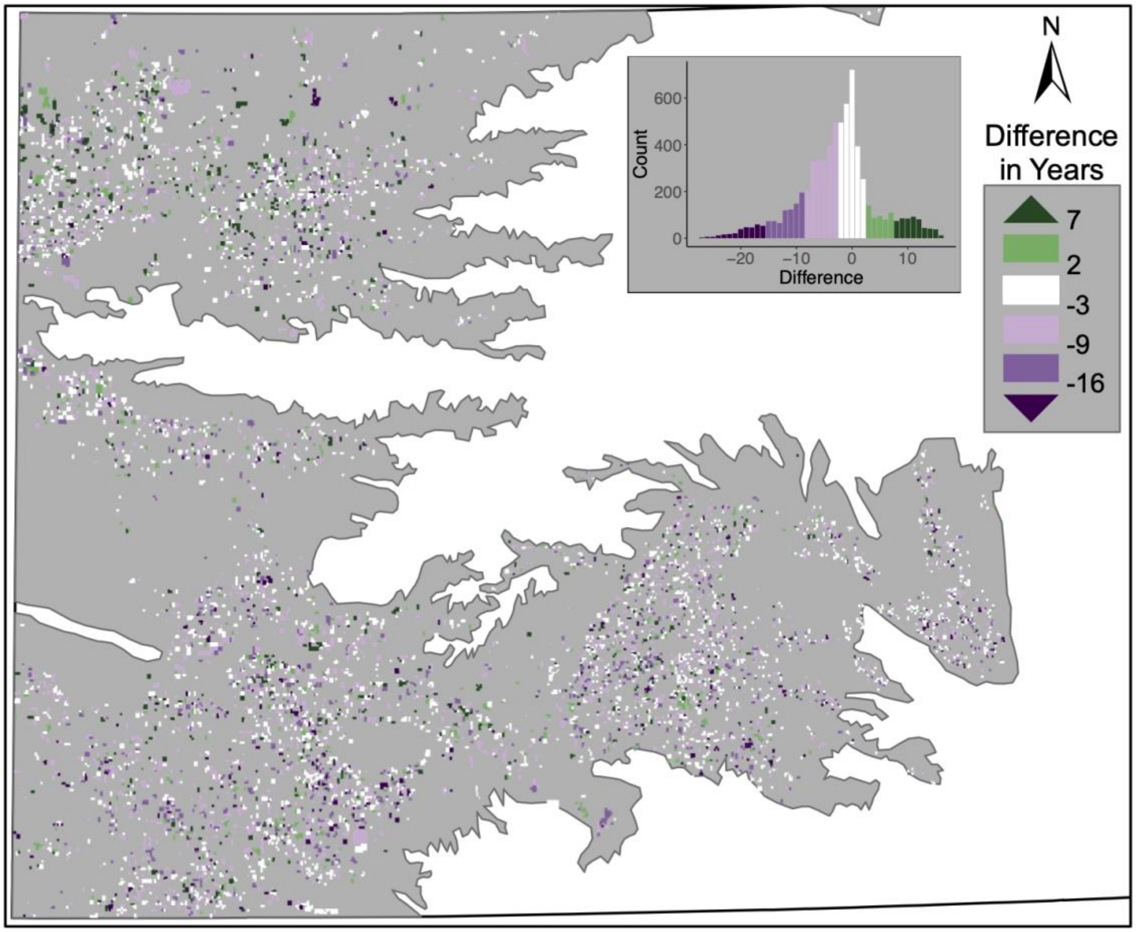

Figure 2.4. Difference between predicted and observed adoption years in Kansas. Differences are mapped approximately, and only the farms with validation data are mapped. Legend and histogram of change point differences, which are calculated by the predicted minus the reported. Negative numbers indicate an early adoption year while positive numbers indicate a late adoption year relative to validation data.

4.1.2. High Plains Aquifer State-Level Validation

Over the entire High Plains Aquifer, we used state-level validation data from the Irrigation and Water Management Survey (USDA NASS, 2017). In this survey, each farmer reports the acreage irrigated by each system in lieu of reporting how many systems each farmer uses. It is probable to assume that farmers use the same irrigation system on multiple fields or use multiple irrigation types on the same field, but the survey does not account for this. Here, we identify irrigation adoption on the farm level. Although our number of irrigated farms per state was significantly higher than the reported number in NASS, the relative adoption statistics were similar, specifically in states that rely heavily on the HPA for agricultural production (Figure 2.5). Through our AIM data, we also have irrigated area information before and after adoption. Although the farms as defined in this study are under the same owner and operator (Farm Service Agency, 2012), it is possible that a farmer owns and operates multiple farms while only reporting information as one farm on the national survey. This makes it difficult to compare adoption counts between validation and prediction datasets. Using relative acreage as validation instead of farm numbers addresses the limitation of mismatching farm definitions. Therefore, we have used relative irrigated area as our primary comparison statistic.

Figure 2.5a shows the farm acreage irrigated by efficient sprinklers in each HPA state through time. Qualitatively, efficient irrigation patterns are best detected in Oklahoma, Kansas, and Texas. Notably, these three states irrigate primarily with groundwater from the High Plains Aquifer (Maupin & Barber, 2005), and most of the irrigated area in these states lies within the HPA. Therefore, state validation data is most representative of our study region in these three states. Predicted irrigation trends closely fitting reported adoption trends in these states shows the potential of this change point detection method. Another possible reason for closer prediction and observed patterns in these states is drier climate. In semi-arid regions, the key differentiator between irrigated and rain-fed crops used to classify remotely-sensed irrigated area, maximum greenness, is more distinct (Ozdogan et al., 2010; Pervez & Brown, 2010; Xu et al., 2019). This also makes patterns derived from remotely sensed irrigation more distinct, which is optimal for our change point method. The opposite is true in humid regions such as Nebraska. The remotely sensed irrigated area used in this study has ample accuracy (92%, Deines et al., 2019), but changes in irrigated area through time are less recognizable in humid regions than in semi-arid regions (Xu et al., 2019).

In states where irrigation is primarily sourced from surface water (Maupin et al., 2014) and the majority of the irrigated area lies outside the study region (Colorado, New Mexico, and Wyoming), our method seems to overestimate the proportion of the state irrigated with efficient irrigation. This is expected, as our study area does not encompass a representative sample of farms in these states. Most farms using irrigation are doing so outside of the HPA and likely use surface water. With the exception of drought induced adoption, efficient irrigation is more frequently implemented in areas with a heavy reliance on groundwater due to the associated costs of drilling wells and pumping groundwater from depth (Schaible & Aillery, 2012; Schuck et al., 2005; Wichelns, 2010). It is expected that farms in our study region will have higher adoption rates thus higher efficiently irrigated area due to the relatively high reliance on groundwater compared to the rest of the state. This is a limitation in the validation data. Survey static summaries are only easily accessible at the coarse spatial resolution of the state level in most places across the US. Irrigation technology data does not properly show the variation of farming practices across the state. It is difficult to assess the effectiveness of conservation programs and integrate irrigation into water use modeling on the local levels without higher spatial resolution information on efficient irrigation practices. It is also difficult to assess whether efficient irrigation makes farming more sustainable on the local level. Higher spatial resolution information of irrigation methods would further constrain and inform decision-making processes. The coarse spatial resolution of readily available validation data further emphasizes the need for a high-resolution dataset of irrigation methods.

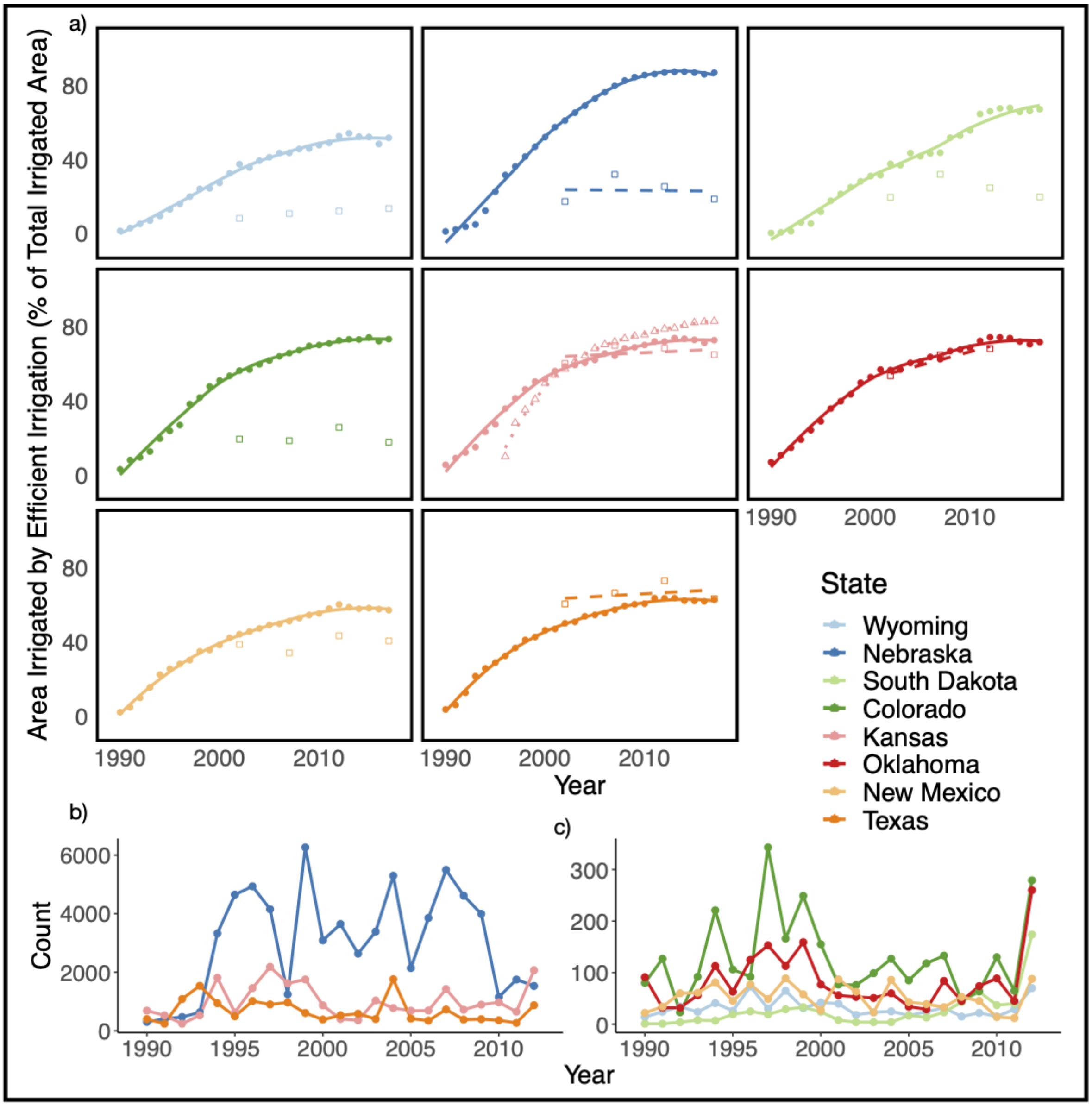

Figure 2.5. Relative area irrigated by efficient sprinkler technology. Efficient irrigation predicted by the change point method and reported on the state level from USDA NASS, 2017. All data is colored using the legend on the right. a) Total area irrigated by efficient sprinkler systems reported as a percentage of total irrigated area through time. Solid LOESS (locally estimated scatterplot smoothing) regression lines and circles denote irrigated area as predicted by change point detection. Dashed traditional linear regression lines and hollow squares indicate USDA survey, self-reported irrigated area. In Kansas, the hollow triangles with the dotted LOESS trend line indicates WIMAS reported irrigated area by wells that had adopted efficient sprinkler irrigation. Trend lines for validation data are only included in states that have most of their irrigated area inside the study region. b) and c) Number of farms adopting efficient sprinkler irrigation methods by year as predicted by change point detection. Note the difference in scales across panels (b) and (c).

4.2. Adoption Trends

Figure 2.5b and c show farm adoption of efficient sprinkler irrigation by year as identified by change point detection. Since our farm units are smaller, our total farm counts are inflated relative to the validation data. That being said, similar patterns are seen in the validation and change point detection data. There is a steep initial increase of adoption in the 1990s in most states, followed by a downward tapering. Efficient sprinkler irrigation was created in the 1980s and spread throughout the 1990s (L. L. New, 1986; Seo et al., 2008). Incentive-based water conservation programs that supplemented the cost of efficient irrigation adoption started on a broad scale in the late 1990s with the 1996 Farm Bill. The change point detection adoption years also show a similar pattern as validation data in that Texas is initially the main adopter, but that later shifts to Nebraska. Overall, it is difficult to compare raw numbers between validation and predicted adoption years for previously discussed reasons, but the similar trends look promising for the use and application of this method.

Predicted adoption years on the farm level are mapped in Figure 2.2. Marginal distributions of adoption year by latitude and longitude show the spatial trends of adopting efficient irrigation. In the south, early adopters are slightly more prevalent than in the north. Efficient irrigation adoption is often utilized as a water conservation method in places that rely on groundwater, and it is often implemented as a method to deter aquifer depletion (Schaible & Aillery, 2012; Seo et al., 2008; Smidt et al., 2016). Semi-arid regions such as the southern HPA have seen extensive aquifer depletion since the 1950s. Texas was also one of the first of the High Plains states to start a conservation program in 1957, called the Texas Water Development Board (TWDB); this was in response to the state’s most severe drought at the time (Winters, 2013). The most notable year of adoption in the south is 2004 (Figure 2.2). This adoption year corresponds to passing of SB 1053 in 2003 that allowed the TWDB to provide subsidies for technology transfers for conservation among other reasons (TWDB, 2004). In the west, the most notable year of adoption is 1996, which corresponds with the passing of the 1996 Farm Bill that included the EQIP to incentivize efficient irrigation adoption. In the west and north, 2007 and 2008 were the most notable years of adoption. This corresponds to drought and legal proceedings in Nebraska that encouraged the adoption of efficient irrigation (Harse, 2009; NOAA, 2017; Punia, 2014; Zeng & Cai, 2014).

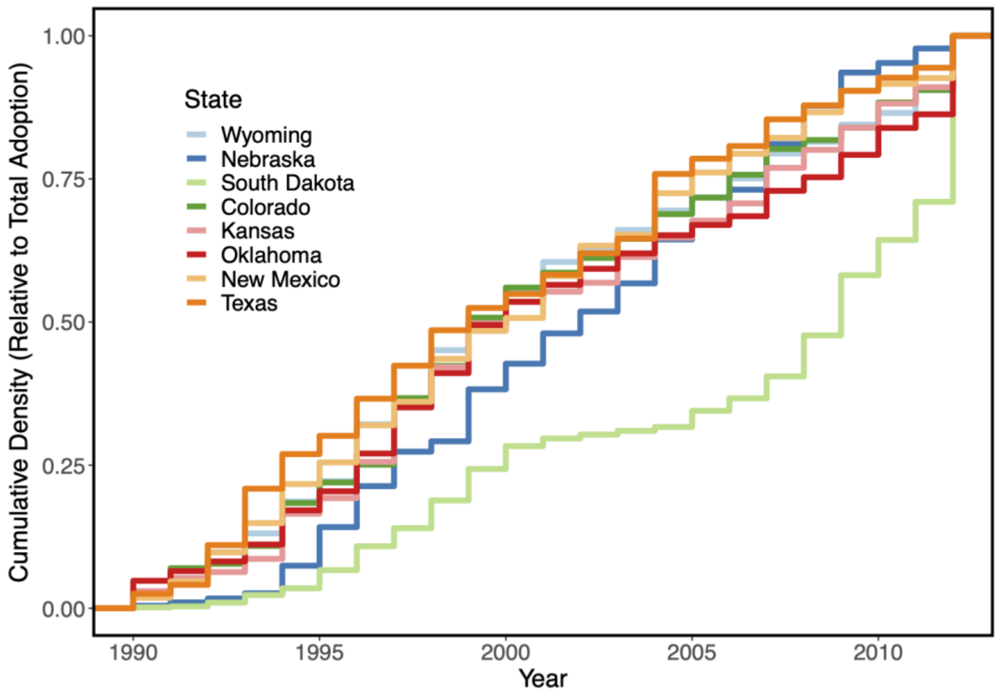

Figure 2.6. Cumulative adoption relative to total adoption through time by state.

In the central HPA region, most of the predicted adoption occurs before 2000, and in the northern high plains' states, adoption is predicted to occur mostly in the last five years of the study period (Figure 2.2). Assessing efficient irrigation adoption through time by state (Figure 2.6) allows for better insight. All adoption trends are qualitatively similar except South Dakota. Southern states such as Texas and Oklahoma are the first to adopt. Nebraska and South Dakota are considerably later to adopt efficient technologies. Since South Dakota sources around half of its irrigation from groundwater, and multiple aquifers exist in the state for pumping, South Dakota is not as water-limited as other states in the study (Amundson, 2002; Carter & Neitzert, 2008). Water stability and lack of incentives often leads to later adoption. The High Plains aquifer underlies both the Pine Ridge and Rosebud Indian Reservations in South Dakota. Intersections between local, state, and tribal water policy and management make for complex water rights and water use (McGuire et al., 2003). This simplified change point detection method does not incorporate effects of policy or tribal farming practices, but it could benefit from this inclusion.

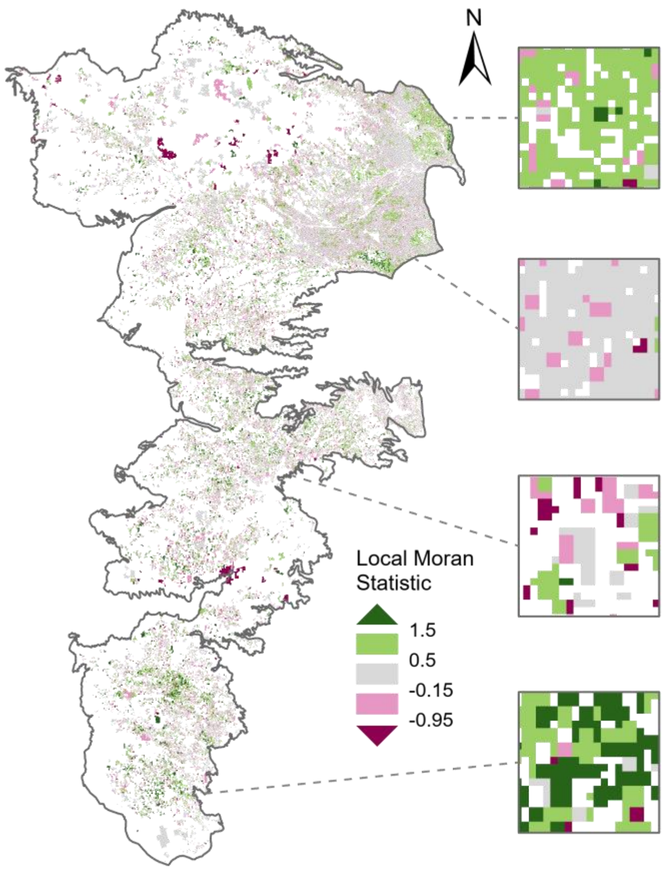

Figure 2.7. Local Moran's I Statistic for predicted efficient irrigation adoption years across the High Plains Aquifer. Positive numbers indicate spatial association of similar years, and negative numbers indicate the spatial dispersion of similar adoption years. Insets (top to bottom): Moderate local clustering with dense adoption, no significant spatial association with dense adoption, variation in local patterns with sparse adoption, significant clustering with dense adoption.

Farmers have been shown to adopt sustainable agricultural practices at higher rates when informed or advised about the practices from neighbors (Krishnan & Patnam, 2014; P. S. Ward et al., 2018). This word-of-mouth transfer of information is likely more tangible and approachable to farmers as opposed to being advised by scientists or extension officers. We see this clustering of efficient irrigation adoption in our change point detected data. Adoption years are significantly clustered globally ($I = 0.25$, $p < 0.0001$), and can be seen locally using Local Moran's *I* statistic. Since this dataset has many points and is spatially dense, the Local Moran's *I* statistic is more helpful and indicative of clustering than the global statistic. The Local Moran's *I* is modified from the global statistic to measure spatial autocorrelation of nearest neighbors (Anselin, 1995). This statistic is a local indicator of spatial association and follows the same conventions as Moran's *I*—positive numbers indicate clustering and negative numbers indicate dispersion. As shown in Figure 2.7, there are clusters of similar adoption years in Texas, central Kansas, and eastern Nebraska. These clusters of similar adoption years are indicative of possible neighbor influence on efficient irrigation adoption.

In Figure 2.8, we normalized irrigation patterns by adoption year to assess linear within-farm irrigation trends before and after adoption. Median irrigated fraction increases, as predicted based in our change point detection method. In all cases, late adopters have a lower irrigated fraction before and after adoption. The very low irrigated fraction in Kansas and Texas indicate that new irrigators may be included more in the late adoption than in the early adoption group. In Texas, early adopters significantly increase their irrigated fraction ($p = 0.012$) prior to adoption, and significantly decrease irrigated fraction ($p = 0.004$) at a lower rate after adoption. This may suggest that early adopters are adopting efficient irrigation for the purpose of irrigation expansion. Late adopters show no significant trends. In Kansas, irrigation patterns show no significant trends prior to or after adoption, which indicates that farmers were likely adopting efficient irrigation for purposes other than irrigated area expansion. Finally, in Nebraska, irrigated fraction increases significantly (all $p < 0.05$) both before and after adoption. This may indicate that Nebraska is less water-limited than the adjacent two states, and farmers in Nebraska are able to increase irrigated area regardless of their irrigation technology. Early adopters in Texas and Kansas show a larger increase in median irrigated fraction than late adopters do. If increasing irrigated area is a driver for farmer adoption in these regions, farmers who adopt earlier benefit more. Changes in irrigation patterns relative to adoption differ across the region. The simplicity of our change point detection method makes it robust and applicable across the ranging climate and irrigation patterns seen in the HPA.

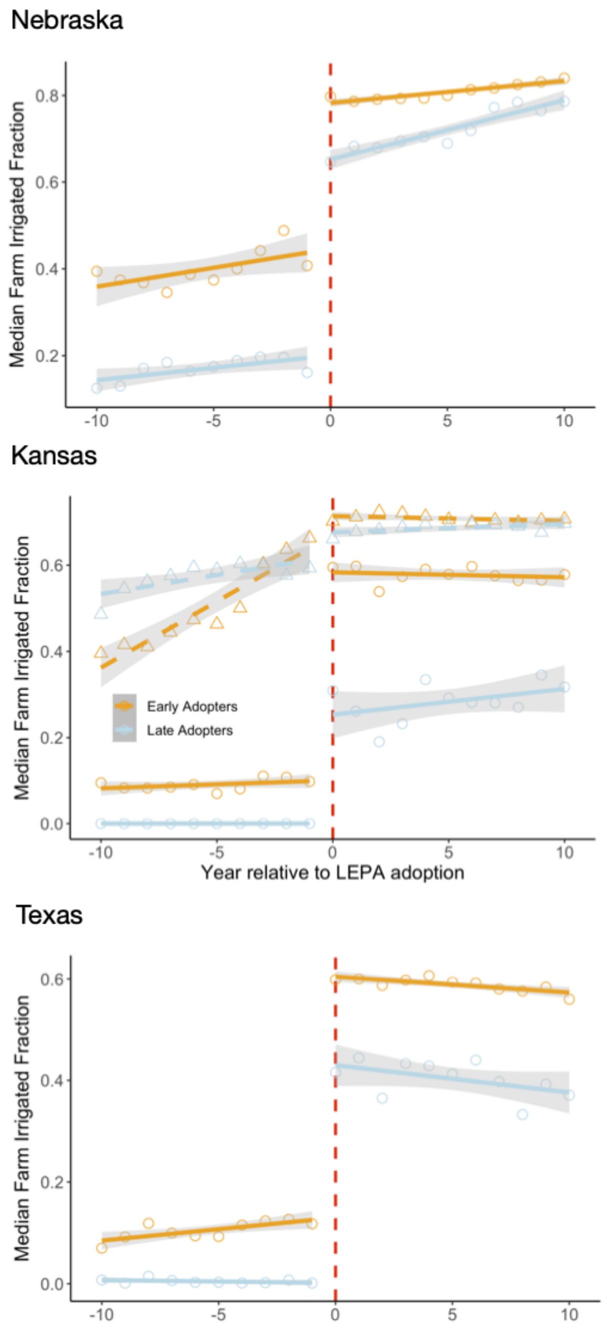

Figure 2.8. Irrigated fraction patterns prior to and after efficient irrigation adoption as detected by the change point method for three selected states. Early adopters are classified as any farm adopting efficient irrigation before 2002 and are colored blue, late adopters are after this and colored orange. Red vertical dashed line indicates the year of adoption, negative years indicate time before adoption and positive years indicate time after adoption. Shaded region shows 95% confidence interval of the linear regression. Note the scales on the y-axis are different between graphs. In Kansas, the dashed lines and triangles represent irrigated fraction relative to WIMAS-derived adoption year.

In the center of Figure 2.8, we show Kansas irrigated fraction relative to efficient irrigation adoption. Patterns relative to adoption predicted by change point detection are in circles, and WIMAS are in triangles. The WIMAS well data has been aggregated to the farm level. For farms with multiple wells that adopted efficient irrigation over time, the most common adoption year was used, adding uncertainty to our data. The WIMAS patterns shown are from all farms with reported adoption of efficient irrigation, and the summary was not limited to farms with correct change point detection results. This likely contributes to the substantial differences. Although our change point detection method worked well on identifying where adoption had occurred, we still had relatively low agreement with validation data to predict when adoption occurred in Kansas (36 percent at +/- 2 years). This may be affected by the relatively later starting year of the validation data. We also see significantly lower irrigated fraction when including all farms that change points have been identified for. The difference in this magnitude is likely due to our definition and normalization of irrigated fraction. Our farms generally have smaller irrigated fraction than farms that include WIMAS wells. This may be because the adjacent farms must transport water, and therefore farmers irrigate smaller fractions of farms. This may also be a limitation due to the mismatch in our definition of farms. As mentioned, only half of the farms with reported irrigation had validation data. Although the magnitude is different, general patterns are similar. The late adopters do not significantly increase irrigated fraction before adoption or after, and their increase in irrigated fraction is not as stark as early adopters. Early adopters show a stronger, significant trend ($p < 0.001$) in the WIMAS data prior to adoption, but the trend is nearly identical after adoption.

4.3. Limitations and Future Opportunities

The change point detection method used here is a simplification of the relationship between irrigated area and efficient sprinkler irrigation adoption. This method is limited to identifying increases in mean irrigated fraction. Although other cost functions are available through the *ruptures* package used here, they were found to be less effective at identifying change points in the study region. This method does not account for external factors of adopting irrigation such as drought (Schuck et al., 2005), policy incentives and water rights (Li & Zhao, 2018), and hydrologic or land characteristics (Caswell & Zilberman, 1986). Further research to incorporate these driving factors would improve the confidence of the change point detection method. Due to its simplicity and flexibility, this method can also be used in tandem with other established models (Carey & Zilberman, 2002; Cortignani & Severini, 2009) to improve accuracy of predicted adoption.

This study was performed on the farm level. Validation data does not currently exist on the farm-level in most states. Datasets used to validate this method currently exist on the state, county, and well-level in the United States. Efforts were made to accurately compare validation and prediction data such as aggregating well information, filtering farm sizes, and normalizing adoption statistics. Limitations still exist for validating irrigation adoption trends in the following ways. Farms defined in this study do not match farms in the validation data. The HPA region does not fully encompass any states, although validation data was compared on a statewide scale. All limitations discussed in the validation data emphasize the importance of this method and its ability to create a dataset of irrigation technologies on the farm-level. With increasing accessibility of high-resolution satellite imagery, (Woodcock et al., 2008; Zhu et al., 2019) agricultural applications of remote sensing are becoming more prevalent (Karthikeyan et al., 2020). There is a need for high-resolution, spatially continuous information on irrigation systems. The dataset resulting from this method has the potential to improve integrated modeling across disciplines.

5. Conclusions

Spatially and temporally explicit information about irrigation technology is a requirement for effective water resource management. Using a change point detection method to identify characteristic changes in irrigation patterns allowed us to create a farm-level dataset of efficient sprinkler irrigation adoption in the High Plains Aquifer region from 1990 to 2012, thus quantifying the spread of LEPA, MESA, LPIC, and LESA during their peak time of adoption. The resulting dataset is applicable in multiple disciplines to further understand conservation irrigation practices and their movement through time in one of the most productive agricultural regions in the United States. Our analysis shows the influence of incentive-based programs and climate factors on efficient irrigation adoption in the HPA. With the inventions of new sustainable irrigation systems such as precision mobile drip irrigation (PMDI), it is difficult to project our adoption rates past the study period. PMDI is a combination of center pivot and drip irrigation launched in the mid-2000s and studies have shown that the pros of this new technology include increased soil water content and dry wheel tracks (Kisekka et al., 2017; O'Shaughnessy & Colaizzi, 2017). Irrigation technology is a dynamic field at the intersection of policy, economy, hydrology, and agriculture. The method used in this study provides a widely applicable dataset to better assess these interactions. As water-levels decline and water scarcity become more pressing (Greve et al., 2018), innovation and adoption of conservative irrigation will be a necessity. The change point detection method used here can be used over irrigation time series data to quantify irrigation technologies. It can also be modified to better assess new and innovative technologies and agricultural practices.

Groundwater withdrawals have substantially increased in the 20th century due to increases in the population and food demand leading to subsequent spread of agriculture to arid and semi-arid regions (Bierkens & Wada, 2019). With an increased reliance on groundwater globally, the consumption of non-renewable groundwater resources has tripled, becoming the source for 20 percent of irrigation (Wada et al., 2012). Irrigation technologies, especially irrigation efficiency, has become a primary tool to combat groundwater declines. To better understand what drives efficient irrigation adoption, we need to know where and when these technologies are implemented. Integrated models to predict water usage require more irrigation technology information to further constrain their predictions. We have shown that a single break point detection method paired with a statistical analysis to provide significance and confidence performs well across a range of temperature and precipitation gradients. Shape recognition on satellite imagery may be a promising future direction to use in tandem with the break point detection. Adding shape recognition to this method would better constrain new adopters from transferring adopters of efficient irrigation technology.

Challenges will still exist in that most new irrigation technologies are modifications to the classic center pivot, meaning the shape will likely stay the same. In this case, assessing greenness and climate factors are other possibilities. The basis for the method used here has been used across disciplines and intentions, which makes the specific method chosen generally transferrable to other signal and time series data. The method used here is also flexible and adaptable to future changes in irrigation technologies and their characteristic effects on irrigation patterns.

Acknowledgments

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