Irrigator Responses to Changes in Water Availability in Idaho’s Snake River Plain

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Thesis submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Master of Science
In
Forestry

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June 19, 2017
Blacksburg, Virginia

Keywords: Agriculture; classification algorithm; irrigation; Snake River Plain; time series;
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ACADEMIC ABSTRACT

Understanding irrigator responses to previous changes in water availability is critical to building effective institutions that allow for efficient and resilient management of water resources in the face of potentially increasing scarcity due to climate change. Using remote sensing data, I examined irrigator responses to seasonal changes in water availability in Idaho’s Snake River Plain over the past 33 years. Google Earth Engine’s high performance cloud computing and big data processing capabilities were used to compare the performance of three spectral indices, three compositing algorithms and two sensors for 2002 and 2007 for distinguishing between irrigated and non-irrigated parcels. We demonstrate that, on average, the seasonal-maximum algorithm yields a 60% reduction in county scale root mean square error (RMSE) over the accepted single-date approach. We use the best performing classification method, a binary threshold of the seasonal maximum of the Normalized Difference Moisture Index (NDMI), to identify irrigated and non-irrigated lands in Idaho’s Snake River Basin for 1984-2016 using Landsat 5-8 data. NDMI of irrigated lands was found to generally increase over time, likely as a result of changes in agricultural practices increasing crop productivity. Furthermore, we find that irrigators with rights to small areas, and those with only surface water rights are more likely to have a major reduction (>25%) in irrigated area and conversely those with a large, groundwater rights are more likely to have major increases (>25%) in the extent of their irrigation.
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GENERAL AUDIENCE ABSTRACT

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Preface/Attribution

Chapter 2 of this thesis “Identifying Irrigated Areas in the Snake River Plain, Idaho: Evaluating Performance across Compositing Algorithms, Spectral Indices, and Sensors” has been accepted for publication in Remote Sensing and will be distributed under the terms and conditions of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/). The copyright is retained by the authors, myself, Kelly Cobourn, Valerie Thomas, Alejandro Flores and Blaine Dawson. All authors took part in the conception and designed the study. I performed the experiments and analyzed the data and drafted the manuscript, which built on the work of Blaine Dawson. My contribution also included the development and implementation of new algorithms in the Google Earth Engine API environment. Kelly Cobourn and Valerie Thomas revised the manuscript and managed the research with the assistance of Alejandro Flores. Support for this chapter was provided by the NASA Land Cover/Land Use Change Program under award NNX14AH15G, a Junior Faculty Award from the Virginia Tech Institute for Critical Technology and Applied Science, and the McIntire-Stennis Cooperative Forestry Research Program.

I would like to acknowledge the guidance provided by Kelly Coburn, Valerie Thomas, Alejandro Flores the reviewers and editors of Remote Sensing, as well as my committee members Kevin McGuire and Randolph Wynne.
Chapter 1. Introduction

Water supply is a major influence on farmers’ decision making and subsequent economic outcomes. Much of the nation’s most productive croplands are located in the arid or semi-arid west where precipitation is limited during the growing season, and irrigation either from surface or groundwater is necessary for many crops to grow. There is pressure on these finite water supplies from a number of directions. Demand for water is increasing from agricultural expansion, urban, industrial and environmental protection uses while water supplies may decline in coming years due to climate change (Chang, 2014; Cobourn, Xu, Lowe, & Mooney, 2013).

Idaho’s Eastern Snake Plain Aquifer (ESPA) (shown in Figure 1-1) is Idaho’s prime agricultural region, and like much of the arid west is dependent on irrigation for crop production. Much of this region often receives virtually no precipitation during the growing (Jerome, ID in the center of the plain received an average of 10 cm of precipitation between the 6 months between April and September, representing 38% of the yearly average total) (NOAA, 2016). Season and irrigation accounts for approximately 84% of the regions water withdrawals and 64% statewide. Relative to other states, Idaho withdraws the nation’s third largest volume of water, and uses the most water per capita (USGS, 2016). Flows in the Snake River have decreased over the past 50 years and the greater Yellowstone snowpack is already declining, and expected to decline further in coming decades due to climate change (Chang, 2014).

1.1 Water Rights

Water allocation in the ESPA, like most western states is based on the prior appropriation doctrine. Water rights allocate specific quantities of water to irrigators, and the date of the water right was issued (referred to as the priority date) dictates its hierarchical rank, where those with older rights have priority over newer ones. A notable difference between Idaho’s water allocation laws and those of most other western states is that in Idaho water rights are tied to specific parcels of land. This potentially poses an additional burden to water rights trading, but it allows for more straightforward geospatial analysis of water rights and water use (Plummer, Rupert, Busenberg, & Schlosser, 2000).

Most irrigators have multiple overlapping water rights and generally have rights to access both surface and ground water. In many cases, there are multiple water rights with identical or
nearly identical spatial extent, while in other cases multiple rights exist for areas that overlap, but have different extents. These overlapping water rights have different characteristics, such as different priority dates, source (groundwater vs. surface water), or may contain an area covered by an irrigation district or other water distributor. In areas covered by irrigation districts, the total water allocation to that irrigation district is available, but we do not have data on the specific allocation of water within each district (other than remotely sensed measures).

Within the ESPA, a large portion of the land with soils suitable for cultivated agriculture is not being used (Figure 1-2A). Rather, the extent of agriculture in this arid region is largely defined by water rights (Figure 1-2B). Most of the areas with rights by no agriculture are urban.

Figure 1-2. Cultivated areas, suitable soils and water rights. Top (A) shows cultivated lands and potato yields. Potato yields are used here as a surrogate for soil productivity, as a generalized soil suitability index was not available, and potato was the crop with the most widely available yield data within the study area. Bottom (B) shows cultivated lands and water rights.
1.2 Prior Studies

A number of prior studies have been completed examining the interplay between water use and water rights in this region. Several of these studies use economic models to assess the impacts of water allocation characteristics on farmers in the ESPA. Xu et al. (2014) examined economic outcomes how the economic outcomes of farmers were impacted by their water rights characteristics. They found that changes in water rights were associated with different responses to seasonal and long term water supply fluctuations and forecasts. Those with Older and thus more secure rights tended to have elevated crop revenue compared to those with less secure rights. However, this study did not identify changes due to shifts in irrigation technology nor did it examine surface-groundwater interactions (Wenchao Xu, 2014; W. Xu, Lowe, & Zhang, 2014).

Xu et al (2015) expounded on previous studies with a focus on irrigation extent. They found that a 1% increase in a farmer’s irrigated area lead to a $18/hectare increase in crop revenue. They also found that crop revenue and irrigation extent were both impacted by long term water stress. Xu predicts that under Idaho’s existing water management, the average irrigation extent and revenues will increase as a result of junior water rights holders will leaving the market due to persistent water shortages (Wenchao Xu & Li, 2015).

Mapping Evapotranspiration at high Resolution with Internalized Calibration (METRIC) is a remote sensing product developed specifically for this study area (Anderson, Allen, Morse, & Kustas, 2012), which is now being applied to other regions. METRIC is a model designed to estimate evapotranspiration based on visible, near infrared, and thermal infrared bands and is typically applied to Landsat imagery (Allen et al., 2013; Morse, Kramber, Allen, & Tasumi, 2004). In Idaho this dataset is being used to quantify recharge for ground water models, as well as to estimate ground water use where pumping data is not available (Allen et al., 2002; Allen, Tasumi, Morse, & Trezza, 2005). Several tests have proven the METRIC dataset to be quite reliable. Comparisons of METRIC and on the ground lysimeter measurements found METRIC estimates to be within +/- 14-16% of the measured values for individual days/images. Much of the error was found to be random, so seasonal estimates are generally more accurate and unbiased. Seasonal measurements were found to be within 1% of measured values (Richard G Allen et al., 2005; Allen, Tasumi, Morse, & Trezza, 2005).

1.3 Preliminary Analysis

In order to develop a better understanding of the factors impacting water use and the potential for water stress in the Snake River Basin, I conducted a preliminary analysis examining water inputs and outputs in the ESPA. Between 2008 and 2011 total water use in the ESPA varied slightly between seasons (+3.1% to -2.4% compared to 2008 levels), while over the same period total stream inflows into the basin showed much larger seasonal variations (+46% to -22% compared to 2008 levels). Comparing inflows of the primary rivers into the Eastern Snake Plain and the total seasonal evapotranspiration illustrates the importance of groundwater use and surface water storage, as nearly twice as much water is used in the ESPA for agriculture as flows in as surface water during the growing season. For instance, in 2011 evapotranspiration used 6.9 million acre feet of water while during the growing season only 3.6 million acre feet of surface water entered the basin. During the 2011 water year approximately 40 million acre feet of precipitation fell within the watershed of the upper Snake River Plain, 8 million acre feet of that water entered the plain through the four primary tributaries (the Henry’s Fork River, Teton Creek, Falls River, and the main stem of the Snake), and 9 million acre feet were discharged as surface water in the Snake (NOAA & NWS, 2016; USGS, 2016).
Additional preliminary analysis was conducted examining water use as measured by METRIC evapotranspiration for the primary crops in the basin to see if water availability could be driving crop choices or vice versa. Water use varies by crop type but there is significant overlap in water use between all crop types (Table 1-1). For the 2011 season sub-irrigator polygons with unique combinations of water rights were analyzed. Only those with composed of 90% or more of a single crop type (based on the CDL) were included, and the average METRIC value was taken for each polygon. These polygon averages were aggregated by crop type and are summarized in Table 1-1. While typical water use varied most between potato and beets, typical water use values for these two crops are still within one standard deviation of each other. The amount of water used is not differentiable by crop type alone and vice versa. Discriminant analysis including additional factor including greenness, crop prices, water rights and water use data was inconclusive. Additional analysis is necessary to successfully model and predict irrigator crop selection.

### Table 1-1. Typical water use by crop type (mm per season in 2011, sub-irrigator units that were>90% single crop).

<table>
<thead>
<tr>
<th>Crop Type</th>
<th>Average</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Count</th>
<th>Water Use (mm) Avg. &amp; Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alfalfa</td>
<td>831</td>
<td>118</td>
<td>277</td>
<td>1,094</td>
<td>427</td>
<td></td>
</tr>
<tr>
<td>Barley</td>
<td>747</td>
<td>75</td>
<td>531</td>
<td>915</td>
<td>111</td>
<td></td>
</tr>
<tr>
<td>Spring Wheat</td>
<td>821</td>
<td>73</td>
<td>548</td>
<td>1,006</td>
<td>356</td>
<td></td>
</tr>
<tr>
<td>Winter Wheat</td>
<td>840</td>
<td>82</td>
<td>512</td>
<td>1,140</td>
<td>271</td>
<td></td>
</tr>
<tr>
<td>Potato</td>
<td>751</td>
<td>72</td>
<td>533</td>
<td>942</td>
<td>335</td>
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<tr>
<td>Sugarbeets</td>
<td>880</td>
<td>56</td>
<td>657</td>
<td>997</td>
<td>161</td>
<td></td>
</tr>
<tr>
<td>Corn</td>
<td>826</td>
<td>89</td>
<td>598</td>
<td>1,027</td>
<td>125</td>
<td></td>
</tr>
<tr>
<td>Other Ag</td>
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</tr>
<tr>
<td>Other Non Ag</td>
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<td>1,216</td>
<td>1329</td>
<td></td>
</tr>
</tbody>
</table>

1.4 Big Data Processing and Cloud Computing of Multitemporal Remote Sensing Data

New developments in cloud computing and big data processing are rapidly changing the way we evaluate, store and process remote sensing data. Previously unmanageable volumes of data can now be handled with relative ease. For instance, the Landsat data archives (the longest running, earth-observing moderate resolution satellite imagery collection) are freely available to the public and consist of over 2 million images covering the entire globe for over 40 years. This represents over 900 terabyte of data, and requires significant resources to store and analyze (Gorelick, 2013). We have access to huge amounts of raw data, but what do we do with it, and how can we process that data and turn it into useful information?

In this study I used the Google Earth Engine (GEE) application programming interface (API) to access and process 33 years of Landsat 5,7 and 8 data. GEE is a cloud computing platform designed to enable petabyte-scale visualization and analysis of geospatial data. GEE also provides access to most freely accessible remote sensing datasets, including the Landsat, and Moderate Resolution Imaging Spectroradiometer (MODIS) archives and higher level data products, all of which is updated daily with new images. The Earth Engine API is a JavaScript platform that allows users to perform complex geospatial analysis such as overlays, map algebra, change detection, classification, vector based image statics extraction and many more functions,
as well as allowing users to create new analyses and combine existing ones. Results are
displayed through an interactive map visualization, but can also be retrieved in charts or exported
as images or tables (Gorelick, 2012, 2013; Moore & Hansen, 2011; Patel et al., 2015).

GEE has two main advantages over conventional desktop based geospatial analysis
programs (such as ESRI’s ArcMap). First, GEE uses cloud computing and parallel processes to
make analyses run orders of magnitude faster than they would on a desktop computer. Second,
the online platform and hosting of geospatial datasets makes it much easier for users to access
and process huge amounts of data (Gorelick, 2013; Wulder & Coops, 2014; Yu & Gong, 2012).
This allows users to simply download the results of their analysis rather than having to download
large volumes of unprocessed data. For instance, the 33-year time series analysis we present in
Chapter 3, consists of 15 Landsat scenes with 13 images during the growing season for each
scene. This translate to approximately 4.1 terabytes of data from approximately 6,400 Landsat
scenes (Wulder et al., 2016). We were able to convert that data into tables of irrigation extent and
intensity by water right and by county which were only 53 megabytes. This is roughly 1/10th the
data volume of a single Landsat image or approximately 1/78,000th the volume of the entire
collection of images used, a reduction 99.9987 %. The 4 terabytes of data used in this study
likely could be processed by a high performance desktop computer (with the aid of external
storage), but processing that information would be slow and largely limited by the speed of the
connection to the externally stored data. It is clear that GEE’s ability to host these large volumes
of data, process them remotely, then allow results to be downloaded is much more efficient for
the user and opens the door to analysis of previously unmanageable size and complexity.

While GEE has several major advantages over conventional programs, it does have some
drawbacks that should be considered. First, the platform is still being developed, so not all of the
features always work as intended, also there is limited technical support and explanatory
resources for many of the functions it can perform. There are several types of analysis that GEE
is currently not particularly well suited for. Vector based data is not well supported, it has to be
uploaded using a third party program, and runs slower than comparably sized raster datasets.
Iteration and recursion is difficult in GEE (as is evident by the code in Appendix B, which
repeats many steps that could be programmed using a recursive function are instead). While it
does well with analysis that can be parallelized, it does not perform well with those that cannot
(such as hydraulic analysis or cell neighborhood statistics) (Gorelick, 2012, 2013; Hancher,
2013; Wulder & Coops, 2014; Yu & Gong, 2012).

In this study I developed new code using the Google Earth Engine API JavaScript
interface. Simplified flowcharts illustrating the analysis performed by this newly developed code
are presented in Figure 1-3 and Figure 1-4. In Chapter 2 GEE is used to compare the
effectiveness of several methods for classifying irrigated and non-irrigated lands in the SRP
(Figure 1-3). I used GEE to access Landsat 5 and MODIS data and applied statistics from that
remote sensing data to a training dataset, from which classification thresholds were developed.
Those thresholds were then applied to the Landsat or MODIS data, from which summary
statistics are calculated and applied to training data and county polygons. Figure 1-4 presents a
simplified summary of the code developed for Chapter 3, where I calculated and applied a
thresholds for 1984-2016 to differentiate between irrigated and non-irrigated lands using Landsat
5, 7 and 8 data. Classified values were summarized and applied to county and water rights
polygons, the results of which were used for further analysis. The code used for the classification
method comparison in Chapter 2 is available at https://github.com/ericwchance/Irrigation_Extent
and the code used for the time series analysis in Chapter 3 is presented in Appendix B.
Since much of the work performed in this analysis was completed using the GEE API, it is easily updated for future growing seasons and can be easily transferred to other time periods.
and regions of the world. No modification of the existing code is necessary to apply our current classification thresholds to any location in the world, but those thresholds are likely region specific. In this study GEE is used to extract values and apply a threshold, but that threshold is calculated outside of GEE. GEE does support several automated classification methods including classification and regression trees, random forests and support vector machine. Incorporating such process into the code used in this study could essentially fully automate the process within GEE making it even more easy to run, and more easy to apply to other regions (Gorelick, 2013; Hancher, 2013; Moore & Hansen, 2011). Essentially, all one would need to transfer the code to another region would be a region specific training dataset. Additionally, fully automating the classification process would allow for much more complex classification schemes (looking at additional image bands as well as creating many more image classes).

The ease transferring and scaling GEE and code to any region of the world in combination with the wealth of Landsat and other data that one can access through GEE makes it an unparalleled resource for large scale geospatial analysis (Erickson, 2014; Gorelick, 2012, 2013; Hancher, 2013; Moore & Hansen, 2011; Patel et al., 2015). With only slight modification and the input of additional training data, it would be possible to develop code in GEE that would classify irrigated and non-irrigated for the entire globe for as far back in time as there is satellite data available. Additionally, the ability to incorporate more complex classification and machine learning could allow future work to easily apply much more complex classification schemes for any and all regions of the globe, and for many more land use/land cover classes. This technology has huge implications for our understanding of land use and land cover changes over time and our ability to map and analyze them at a fine spatial scale. This new ability to look at and understand global scale changes will have major impacts on our predications of climate change and other large scale natural processes. Future research will undoubtedly aim to refine our understanding of these land use/land cover changes, and apply that information to land management and societal problems like sea level rise, and adaptations to climate change.

1.5 Objectives

The goal of this study is to evaluate the impacts of changes in water availability on irrigator behavior in the ESPA and to understand if certain irrigator behaviors are associated with different levels of water availability. First, I develop the geospatial datasets necessary to determine the impacts of past changes in water availability on irrigator behavior in terms of intensive and extensive water use. In order to assess irrigator responses to changes in water availability I:

1. Quantify wetness and greenness indicators over time (as a proxy for water use and crop productivity).
2. Examine changes in irrigation extent over time.
3. Assess the relationship between greenness indicators and water availability over time.

These results can then be used for future research to evaluate the impact of changes in water availability due to climate change on irrigator behavior in this region.
Chapter 2.

Chapter 2 of this thesis has been published in Remote Sensing. It is reproduced here, beginning on the following page.

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Abstract: There are pressing concerns about the interplay between agricultural productivity, water demand, and water availability in semi-arid to arid regions of the world. Currently, irrigated agriculture is the dominant water user in these regions and is estimated to consume approximately 80% of the world’s diverted freshwater resources. We develop an improved irrigated land-use mapping algorithm that uses the seasonal maximum value of a spectral index to distinguish between irrigated and non-irrigated parcels in Idaho’s Snake River Plain. We compare this approach to two alternative algorithms that differentiate between irrigated and non-irrigated parcels using spectral index values at a single date or the area beneath spectral index trajectories for the duration of the agricultural growing season. Using six different pixel and county-scale error metrics, we evaluate the performance of these three algorithms across all possible combinations of two growing seasons (2002 and 2007), two datasets (MODIS and Landsat 5), and three spectral indices, the Normalized Difference Vegetation Index, Enhanced Vegetation Index and Normalized Difference Moisture Index (NDVI, EVI, and NDMI). We demonstrate that, on average, the seasonal-maximum algorithm yields an improvement in classification accuracy over the accepted single-date approach, and that the average improvement under this approach is a 60% reduction in county scale root mean square error (RMSE), and modest improvements of overall accuracy in the pixel scale validation. The greater accuracy of the seasonal-maximum algorithm is primarily due to its ability to correctly classify non-irrigated lands in riparian and developed areas of the study region.

Keywords: agriculture; classification algorithm; irrigation; Snake River Plain; water use

1. Introduction

Semi-arid and arid regions cover nearly 41% of the Earth’s surface and are home to more than 38% of the population [1]. These regions typically receive limited precipitation during the agricultural growing season of April to October, averaging 0.1–0.8 m annually, and experience hotter, drier summers than other regions of the world [2]. Most vegetation is likely to be dead or in a stage of senescence during the hot summer months unless supplemental water is available for plant consumption. As a result, semi-arid and arid regions rely heavily on irrigation to support agriculture. For example, in the western United States, agriculture accounts for over 90% of consumptive groundwater and surface water use [3]. The 17
conterminous western states alone account for 85% of water withdrawals in the United States and 74% of irrigated acres, with the states of California, Texas, and Idaho consistently leading the nation in total water withdrawals [3]. Given the reliance of these regions on irrigation, it is essential to develop an understanding of spatial and temporal patterns of water use and food production. In addition to the food security implications, use of irrigation in the agricultural landscape is of particular interest because it affects groundwater quality and quantity, ecological processes, climate, and biogeochemical and hydrologic cycles [4].

Accurate mapping of the distribution of irrigated land at a regional scale can facilitate an improved understanding of patterns of water use and food production on an annual to decadal basis. As the frequency of precipitation events declines during the summer months, anomalies in plant greenness or water content can be attributed to irrigation practices. Specifically, the presence of green, healthy vegetation during the summer growing season can most likely be attributed to irrigation water applications [5]. Remote sensing yields a source of readily available data that can be used to identify and quantify irrigated area on an annual timescale based on within-season trends in greenness. In particular, the Normalized Difference Vegetation Index (NDVI), derived using near infrared and red reflectance, has been used for mapping irrigated areas on the local scale and is effective because of differential spectral responses between irrigated and non-irrigated croplands [6].

Using NDVI as an indicator of vegetation phenology reduces the amount of computational storage needed, improves processing time, and provides a simple means for classifying complex landscapes [7]. There is overwhelming agreement that NDVI can be a vegetation monitoring tool [8-11]. NDVI and plant moisture availability are closely related [12], which makes NDVI a sufficiently good indicator of irrigation presence [13-16]. Studies using NDVI have been used to distinguish irrigated from non-irrigated land use in semi-arid and arid regions in India and Turkey [5, 7, 17]. NDVI has also been used to classify land use and land cover in which irrigated area is one of multiple classification categories [4, 18, 19].

Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat have been found to be the most effective imagery for observing differences in NDVI in semi-arid and arid regions [6]. The MODIS instrument, aboard NASA’s Aqua and Terra satellites, has been applied to map land use using multiple reflectance spectra and vegetation indices [17, 20]. Likewise, the Landsat remote sensing system has proven a useful tool for producing land-use maps [21, 22]. Each of these remote sensing products has its spatial and temporal advantages and disadvantages: MODIS gathers higher-frequency, daily data, but at a relatively coarse, 250-m or 500-m spatial resolution, whereas Landsat has a lower-frequency return interval of approximately 16 days, but a relatively fine, 30-m spatial resolution. A shorter return interval is advantageous when cloud cover renders some images during the agricultural growing season unusable; a finer spatial resolution is advantageous because it captures water use patterns at the scale of the individual field.

Ozdogan et al. [5, 6] demonstrate that using a single observation date for NDVI, preferably during the peak of the growing season, is sufficient for distinguishing irrigated from non-irrigated land use using Landsat data in southeastern Turkey. When applying this method to other regions, however, classification errors may arise if farmers use inconsistent harvesting and irrigation practices. For example, alfalfa may be harvested multiple times throughout the growing season, potentially lowering its NDVI (and other index) values just after harvest. Likewise, irrigated water may have been cut off before the selected single image date, again potentially lowering NDVI values. Moreover, the optimal choice of observation date may differ across space and across years due to differences in summer precipitation events, for example.

To address these challenges, we test methods that have the potential to identify areas that are irrigated at any point throughout the entire growing season. We thus introduce methods that extend the window of observation from a single date to a time interval that captures within-season differences in greenness trajectories between irrigated and non-irrigated sites. We evaluate two new algorithms and the existing, single-date algorithm from Ozdogan et al. [5, 6] for classifying irrigated lands in semi-arid and arid regions.
using multispectral data from both MODIS and Landsat. The two new algorithms classify land use based on summary statistics that describe the trajectory of greenness over the duration of the growing season (April to October). The first, which we call the greenness-duration approach, develops a threshold based on the difference in area below the spectral index curve for irrigated and non-irrigated sites. The second, which we call the seasonal maximum approach, develops a threshold based on the difference in the maximum of each spectral index between irrigated and non-irrigated sites (where the maximum for each index may fall on a different date). These new algorithms and the single-date algorithm are implemented using three vegetation indices—The Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and the Normalized Difference Moisture Index (NDMI)—derived from both MODIS and Landsat imagery. Our objective is to contrast the performance of each algorithm-spectral index-dataset combination in terms of classification accuracy and to quantify the spatiotemporal patterns of irrigated land in our study region.

2. Study Region

Our study region is the counties containing the Snake River Plain (SRP) of Idaho, United States (Figure 1). The region is approximately 500 km east to west, and spans the majority of southern Idaho. The SRP has a Mediterranean-style semi-arid to arid climate in which the summer months have lower precipitation compared to other months of the year. The entire study area exhibits a “summer dry” climate, which allows us to explore methods to map irrigated land use via changes to the Earth’s surface reflectance spectra caused by irrigation. However, there are significant differences in elevation, temperatures, and precipitation between the western and eastern SRP (distinguished by a black line in Figure 1). Relative to the eastern portion of the SRP, the western portion is at a higher elevation, with generally higher temperatures and more precipitation. Mean annual temperature is at its maximum in the western portion of the Snake Plain at 13 °C, and precipitation generally increases west to east from approximately 25 cm annually to 35 cm annually, the majority of this comes during winter months. Much lower temperatures and higher precipitations occur on the surrounding mountains. Elevations of the plain vary from approximately 680 m above sea level in the west to 1680 m in the east (higher elevations can be found in adjacent mountain peaks, several of which are in excess of 2800 m). Differences in climate between the eastern and western portions of the SRP are primarily controlled by Pacific Ocean-derived moisture and topography [23].
Figure 1. Map of the Snake River Plain (SRP). The Study area consists of the counties containing the SRP with large forested areas removed. Counties in the East Snake Plain are shown in a darker red than those in the west.

In the SRP, agricultural productivity, the value of agricultural land, and farmers’ land-use decisions are driven by the availability of water for irrigation. Idaho alone ranks third in the United States in terms of the volume of water withdrawn, and first in terms of water withdrawals per capita [24]. Over 98% of all water withdrawn in Idaho goes to counties that lie completely or partially within the SRP, with the majority of that water, 85.6%, used for irrigation [25]. Based on the 2011 USDA Cropland Data Layer, within the SRP’s cultivated lands 28% was growing spring and winter wheat, 26% was alfalfa, 12% was barley, 10% was corn, 10% was potato, 6% was sugar beet, 2% was dry beans and 4% was growing other crops. Approximately 20% of the study region is in agriculture. Water for irrigation is supplied predominantly by winter snowpack, rendering this region particularly vulnerable to the effects of climate change [26]. Recent research shows that climate has already begun to impact the timing of snowmelt runoff and suggests increased variability in the timing and magnitude of available water derived from winter snowmelt in the future [27]. Increased variability in water resources during the late summer months, at a time when water is critical for crop growth, will introduce uncertainty into agricultural production. This uncertainty is likely to influence land-use patterns, and thus the economy, hydrology, and ecology of the region.

3. Materials and Methods

As is evident in Figure 1, our study area is relatively large and encompasses multiple Landsat scenes (i.e., Landsat paths 38–42 and rows 29–31). For the multitemporal Landsat analysis, this introduces “big data” computational challenges, with large data volumes (terabytes) and high performance computing requirements for image processing. Therefore, we utilize the Google Earth Engine API platform for our multitemporal algorithms. As part of the platform, Google maintains the Landsat and MODIS satellite archives, with Landsat data pre-processed to reflectance. Using this interface, we use the Landsat reflectance products with masked clouds identified by the Fmask algorithm [28]. Our index calculations and algorithm computations are also performed in this environment. 
3.1. Vegetation and Plant-Water Indices at High and Moderate Spatial Resolutions

This study classifies irrigated land using two common vegetation mapping indices (i.e., NDVI and EVI) and a plant–water index, NDMI, which is designed to be more sensitive to changes in canopy water content.

NDVI is defined as:

$$\text{NDVI} = \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + \rho_{\text{red}}}$$  \hspace{1cm} (1)

where $\rho_{\text{nir}}$ and $\rho_{\text{red}}$ represent near infrared and red reflectances, respectively [29]. EVI is a refined version of NDVI that corrects for additional atmospheric influences, reduces saturation, and accounts for canopy effects [20, 30, 31]. EVI is defined as:

$$\text{EVI} = G \times \left( \frac{(\rho_{\text{nir}} - \rho_{\text{red}})}{(\rho_{\text{nir}} + C_1 \times \rho_{\text{red}} - C_2 \times \rho_{\text{blue}} + L)} \right)$$ \hspace{1cm} (2)

where $G$, $C_1$, $C_2$ and $L$ are sensor-specific constants for gain ($G$), aerosol resistance ($C_1$ and $C_2$), and a canopy adjustment term ($L$).

NDMI, also referred to as the Normalized Difference Water Index (NDWI), is defined as:

$$\text{NDMI} = \frac{\rho_{\text{nir}} - \rho_{\text{swir1}}}{\rho_{\text{nir}} + \rho_{\text{swir1}}}$$ \hspace{1cm} (3)

where $\rho_{\text{swir1}}$ represents short wave infrared (1.55–1.75 $\mu$m) reflectance [32].

We calculate each index at high (Landsat, 30-m) and moderate (MODIS, 250-m and 500-m) spatial resolution. Table 1 provides a summary of the data products used in this study. The MODIS global data product (MOD13Q1) includes cloud-free 16-day mosaics of NDVI and EVI. Landsat 5 surface reflectance (SR) data were used to provide high resolution versions of NDVI, EVI, and NDMI. Existing NDVI, EVI, and NDMI cloud-free 32-day top of atmosphere (TOA) composites were used (LT5_LIT_32DAY, provided by Google Earth Engine). It should be noted that the size of the study area necessitated using images composited over several days for the single date approach in order to get a single image that covers the study area. In addition, the Google composites generally use the most recent image in the given time period unless it is cloud impacted. Table A1 lists the start date of each composite used.

<table>
<thead>
<tr>
<th>Table 1. Summary of remote sensing products tested including data provider, dataset name, compositing description, and spatial resolution.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Single Date</strong></td>
</tr>
<tr>
<td>MODIS NDVI</td>
</tr>
<tr>
<td>MODIS EVI</td>
</tr>
<tr>
<td>MODIS NDMI</td>
</tr>
<tr>
<td>Landsat 5 NDVI</td>
</tr>
<tr>
<td>Landsat 5 EVI</td>
</tr>
<tr>
<td>Landsat 5 NDMI</td>
</tr>
</tbody>
</table>

3.2. Development of a Training Dataset

A training dataset of known land-use points was developed using manual interpretation of the National Agriculture Imagery Product (NAIP), which consists of high resolution aerial photographs. In our study region, NAIP images are available for the 2003, 2004, 2006, and 2009 growing seasons. Approximately 10 irrigated and 10 non-irrigated points were identified within each of 21 counties. The final training dataset contains a total of 404 control points. Points were generally located near the center of fields or away from
edge areas to avoid mixed pixels, however for the at the 500 m resolution of some of the MODIS data some mixing is likely inevitable. Figure 2 illustrates these control points as well as several example points for Twin Falls County in 2007.

Figure 2. (Top) Irrigated and non-irrigated control points, overlain on top of 2007 Landsat 5 imagery for the study region. (Bottom) Enlarged section to illustrate irrigated and non-irrigated areas for several control points.

3.3. Three Pixel-Scale Thresholding Approaches for Classification

We investigate three classification algorithms using each of the spectral indices (NDVI, EVI and NDMI) developed using data from MODIS and Landsat 5. Each algorithm is implemented for two years—the 2002 and 2007 growing seasons. The classification itself is performed at the scale of the individual pixel. We report classification accuracy metrics at this spatial scale for each algorithm-index-dataset combination. In addition, the years 2002 and 2007 correspond to the years of the USDA Agricultural Census, which allows us to use aggregate, county level statistics as a second benchmark against which we test the classification accuracy of each algorithm-spectral index-dataset combination.

3.3.1. Single-Date Algorithm

The first algorithm uses single-date imagery, as in Ozdogan et al. [5, 6]. This method requires that we first determine the observation date at which the difference in the spectral index value between irrigated and non-irrigated land is at its maximum. The date at which the maximum difference in the spectral index between irrigated and non-irrigated pixels is observed is illustrated conceptually for NDVI by the vertical black arrow in Figure 3 (the conceptual diagram is the same for EVI and NDMI). For each year we select the composite image for which the irrigated and non-irrigated index values are at their greatest separation by calculating the difference between the sum of all spectral index values for the training dataset of known irrigated points and the sum for non-irrigated points for each available image date within the growing season. As discussed by Ozdogan et al. [5], the best window to apply this classification scheme is near the timing of peak green-up.
Figure 3. Diagram of example irrigated and non-irrigated Normalized Difference Vegetation Index (NDVI) curves with metrics used for image classification noted. NDVI is shown; Enhanced Vegetation Index (EVI) and Normalized Difference Moisture Index (NDMI) are similar.

We then derive a threshold value that maximizes classification accuracy for both land-use categories. To do so, we fit a separate nonparametric kernel density function to the observed spectral index values for irrigated and non-irrigated control points in the training dataset. This is done using the kdensity function in Matlab, which uses a frequency of 1/100th the range of the data. Using those fitted distributions, we calculate the probability that a pixel is irrigated or non-irrigated at a range of potential threshold values based on both kernel density functions. We select the threshold value at which the probability of classifying the pixel as irrigated or non-irrigated is equal, which represents the point at which the fitted normal kernel density functions intersect (which simultaneously minimizes type II error for both distributions). Observations above the threshold are classified as irrigated; those below the threshold are classified as non-irrigated. Threshold values used for each year and classification method are listed in Appendix A (Table A1).

3.3.2. Greenness-Duration Algorithm

The second thresholding method distinguishes irrigated from non-irrigated land using the area under a spectral index curve over the duration of the growing season, rather than at a single date. The differences in the areas under the spectral index curve for irrigated and non-irrigated points are illustrated for NDVI with cross-hatching in Figure 3. The area under each spectral index curve is computed by calculating the integral of the time series from 1 April to 31 October and deriving the threshold value that most accurately classifies both land-use categories using the same probability based approach used for the single-date algorithm.

Peak green-up, the time at which crops are at or nearly at their maximum index values, typically occurs in mid-summer. However, using the greenness-duration approach, we find that the greatest difference in the areas under the spectral index curves tends to fall later in the growing season. This occurs because
following peak green-up, non-irrigated crops typically begin to show a reduction in vegetation index values while irrigated control point values maintain elevated levels for multiple images.

This approach also mitigates some classification error that arises when crops are harvested multiple times during the growing season, such as alfalfa, which is one of the top crops grown in the SRP. Irrigated alfalfa may be harvested 4–5 times during a growing season, while dryland alfalfa yields fewer cuttings. Multiple cuttings result in multiple peaks in spectral indices during the growing season, muddying the signal in peak green-up for the single-date approach. By accounting for the area under the curves, the greenness-duration approach better captures the difference in spectral index for irrigated and non-irrigated crops across multiple cuttings.

3.3.3. Seasonal-Maximum Algorithm

In our third approach, we use a single threshold value for the region based on the seasonal maximum for each spectral index, where both the date and the level of the seasonal maximum of irrigated crops may differ from that of non-irrigated crops, as illustrated in Figure 3. We compute the seasonal maximum for each growing season (again defined as 1 April to 31 October) in Google Earth Engine. Here we use the same probability based approach to select the optimal threshold as described for the single-date and greenness-duration algorithms.

When using the Landsat NDMI data for this algorithm, error may be introduced into the classification due to variability in NDMI from climate, farm equipment, or other anomalies. To address this challenge and increase the reliability of the training dataset for this particular algorithm-index-dataset combination, we extract a nine-pixel square around each control point. We remove from the dataset any pixel values outside two standard deviations of the mean NDMI within the nine-pixel square. We also control for differences in climate across the study region through the inclusion of average annual precipitation data for each control point or nine-pixel square [33]. We use average precipitation data because spatially explicit annual precipitation data are not available for the entire study period. Using discriminant analysis for the 2003 growing season, we test the effect of controlling for precipitation.

3.4. Validation and Accuracy Assessment

We validate the classification from each algorithm-index-dataset combination at the individual pixel level using two different validation datasets. The first (which we refer to as the symmetrical validation dataset) uses 75 known irrigated and 75 known non-irrigated points. The second validation dataset (which we refer to as the supplemental land-use validation dataset) uses NAIP imagery to differentiate between irrigated land and multiple non-irrigated land uses, including dryland agriculture and development. In addition to these pixel-scale validation approaches, we compare the classified area in irrigated and dryland agriculture to county level statistics from the USDA Census of Agriculture.

For the pixel-scale symmetrical validation dataset, we create a sample dataset of randomly selected points in the region and determine whether they are irrigated or non-irrigated agriculture in 2002 and 2007 using NAIP and Google Earth imagery. We supplement this dataset with randomly generated points that lie within the geospatial boundaries of the place of use for prior appropriation water rights [34]. Farmers are restricted to applying water for irrigation within the place of use specified as part of a water right [35, 36]. Using these supplementary data facilitate the process of identifying control points that are irrigated. Large forested areas, which mainly occur along the outer edge of the study region, are hand-delineated and removed from the analysis to attain an appropriate measure of accuracy in classifying irrigated area. In comparison to irrigated NDVI trends, the NDVI values of forested locations show far less variability than irrigated land use over the same time period.

From a randomly selected sample of potential validation points, we exclude points that were primarily in agricultural areas that appeared, based on NAIP imagery, to have been non-irrigated at some point
between 2002 and 2007. In addition, we exclude points for which it is unclear whether they are irrigated or
non-irrigated. Examples include areas with visible irrigation infrastructure where the crops appeared non-
irrigated or areas where no visible irrigation infrastructure was present but the crops were greener than
nearby nonagricultural areas. We also exclude points that are close to the edge of a field or points that
contain multiple land-use types. The final pixel-level symmetrical validation dataset contains 150 points
(75 irrigated and 75 non-irrigated) that can be definitively identified as irrigated or non-irrigated for our
entire study period. We use these selected points to generate a confusion matrix with commonly used
classification accuracy metrics, including overall accuracy, user’s accuracy, producer’s accuracy, and the
kappa coefficient, as a comparison of the observed accuracy to random chance.

For the pixel-scale supplementary land use validation dataset, we randomly select 320 points in the
study region, 20% of which are irrigated or dryland agriculture, and 3% of which are suburban or urban
development. This land-use composition is representative of the region based on the 2006 National Land
Cover Dataset [37]. We use NAIP imagery to determine land cover for 2007, but areas that are not irrigated
are broken down into four classes: desert (sparsely vegetated), non-agricultural but vegetated (green areas,
usually riparian or covered with woody vegetation), dryland (non-irrigated) agriculture, and developed
(urban and suburban areas). Points are only adjusted if they were too close to the edge of a field, or to
ensure that there were representative proportions of agriculture, non-agriculture, and developed lands
(20% agriculture, 3% developed and 77% other). The percentage of points correctly classified in each of
these categories is calculated, as well as the overall percent correctly classified.

As an additional assessment of our results, we compare our findings to data from the USDA Census
of Agriculture. Here, we calculate irrigated and non-irrigated areas by county for each year and compare
our area total to that from the USDA Census of Agriculture for the years 2002 and 2007. The Census data
are based on surveys of individual farmers, but is reported at the county scale. This provides an
independent third-party assessment of our algorithm-index-dataset combinations. We compute the
coefficient of determination (R²) as an indication of the variance of the area reported in the Census that is
explained by our model outputs. We also report the root mean squared error (RMSE) as a measure of the
difference in predicted irrigated area relative to USDA Census statistics.

4. Results

With a combination of three algorithms (single date, greenness duration, and seasonal maximum),
three spectral indices (NDVI, EVI, and NDMI), two remote sensing datasets (Landsat 5 and MODIS), and
two years (2002 and 2007), the results from this analysis (36 products) are too numerous to fully display
here. Instead, we present summary statistics describing classification accuracy for all cases using the pixel-
scale symmetrical validation dataset and county scale Census data in Tables 2–4 and the supplementary
pixel-scale land use validation dataset in Table 5. In addition, we present Landsat-derived NDMI maps of
irrigated lands in 2007 for each of the three algorithms (Figures 4 and 5). An equivalent to Figure 4 showing
MODIS NDMI maps for 2007 is presented in Figure A1 in the Appendix. We choose this particular
combination to map as a representative example of classification patterns produced by each classification
algorithm.
Figure 4. The 2007 irrigated areas classified using Landsat 5 NDMI for the three algorithms: (A) single date algorithm; (B) greenness duration algorithm; and (C) seasonal-maximum algorithm. Non-irrigated areas are shown in white, irrigated areas are green and masked areas outside the study region are grey.

4.1. Single-Date Algorithm

Figure 4A illustrates the 2007 Landsat-derived NDMI map using the single-date approach. The spatial pattern of irrigated lands produced by the algorithm corresponds to general spatial patterns in irrigated production throughout the study region. The majority of irrigated agricultural production follows the arc of the Snake River across the Plain. There are three predominant sub-regions in which irrigated production occurs: the northeastern portion of the Plain, fed by surface water flowing from the headwaters in Yellowstone National Park to the American Falls Reservoir; the south-central portion of the Plain (also called the Magic Valley), which is fed by springs from the Eastern Snake Plain Aquifer and extends to the western edge of the Eastern Snake Plain; and the Ada/Canyon County area in the northwestern corner of
the Plain, which is home to much of the region’s specialized crop production, including viticulture and orchard crops. There are several linear artifacts in the northeast portion of Figure 4A that are a result of poor cloud removal in the 32 day composite created Google.

Table 2 presents pixel-level and county-level accuracy assessment statistics for the single-date algorithm by growing season, dataset, and spectral index. The pixel-level accuracy statistics are calculated using the symmetrical validation dataset. At the pixel scale, classifications based on Landsat data slightly outperform those produced with MODIS data across years and spectral indices. For example, using NDMI as the spectral index in 2002, the overall accuracy using Landsat is 97.3% with a kappa of 0.947; for MODIS, the corresponding statistics are 96% and 0.920. At the county scale, the opposite holds: the results favor a classification approach using MODIS data. For example, MODIS produces an $R^2$ of 0.920 and 0.948 for NDMI in 2002 and 2007, respectively, while Landsat produces an $R^2$ of 0.839 and 0.777 for the same index and years. The results using RMSE as a measure of county scale accuracy similarly favor MODIS, potentially because of MODIS’s higher temporal resolution, it may be more likely to capture an image closer to the date of peak greenness.

Table 2. Single-date algorithm accuracy statistics. Producer’s and user’s accuracies are for the irrigated class. Coefficient of determination ($R^2$) and root mean square error (RMSE) are calculated at the county scale.

<table>
<thead>
<tr>
<th>Year</th>
<th>Dataset</th>
<th>Index</th>
<th>Overall Accuracy (%)</th>
<th>Producer’s Accuracy (%)</th>
<th>User’s Accuracy (%)</th>
<th>Kappa</th>
<th>$R^2$</th>
<th>RMSE (km$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>Landsat</td>
<td>NDVI</td>
<td>90.0</td>
<td>81.3</td>
<td>98.4</td>
<td>0.800</td>
<td>0.676</td>
<td>281</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>92.0</td>
<td>84.0</td>
<td>100.0</td>
<td>0.840</td>
<td>0.771</td>
<td>237</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>97.3</td>
<td>97.3</td>
<td>97.3</td>
<td>0.947</td>
<td>0.839</td>
<td>350</td>
</tr>
<tr>
<td></td>
<td>MODIS</td>
<td>NDVI</td>
<td>86.0</td>
<td>72.0</td>
<td>100.0</td>
<td>0.720</td>
<td>0.893</td>
<td>118</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>87.3</td>
<td>74.7</td>
<td>100.0</td>
<td>0.747</td>
<td>0.910</td>
<td>160</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>96.0</td>
<td>94.7</td>
<td>97.3</td>
<td>0.920</td>
<td>0.920</td>
<td>298</td>
</tr>
<tr>
<td>2007</td>
<td>Landsat</td>
<td>NDVI</td>
<td>99.3</td>
<td>98.7</td>
<td>100.0</td>
<td>0.987</td>
<td>0.733</td>
<td>309</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>99.3</td>
<td>98.7</td>
<td>100.0</td>
<td>0.987</td>
<td>0.838</td>
<td>268</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>91.3</td>
<td>84.0</td>
<td>98.4</td>
<td>0.827</td>
<td>0.777</td>
<td>290</td>
</tr>
<tr>
<td></td>
<td>MODIS</td>
<td>NDVI</td>
<td>89.3</td>
<td>80.0</td>
<td>98.4</td>
<td>0.787</td>
<td>0.873</td>
<td>300</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>98.7</td>
<td>98.7</td>
<td>98.7</td>
<td>0.973</td>
<td>0.757</td>
<td>490</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>96.0</td>
<td>94.7</td>
<td>97.3</td>
<td>0.920</td>
<td>0.948</td>
<td>255</td>
</tr>
</tbody>
</table>

Across spectral indices, there are significant differences in classification accuracy (see Appendix Tables A4 and A5 for pixel scale significance levels across compositing algorithms and spectral indices, because of the large sample size, all differences in county scale performance are significant based on a z score test and a critical level of 0.05). Using the single date algorithm, the index that produces the highest accuracy differs across datasets and years. In the majority of cases, NDMI and EVI outperform NDVI. Across years, datasets, and accuracy metrics, NDVI often produces the lowest classification accuracies, particularly at the county scale. The exception is for 2007, in which NDVI and EVI produce an identical pixel-scale overall accuracy of 99.3% and outperform NDMI, which produces an overall classification accuracy of only 91.3%. For MODIS data, the highest accuracy metrics are obtained using NDMI. At the county scale, NDMI outperforms NDVI and EVI for $R^2$, though the results are mixed when using RMSE as the accuracy metric.

4.2. Greenness-Duration Algorithm

The 2007 Landsat-derived NDMI map using the greenness-duration approach is shown in Figure 4B. With respect to location in the SRP, the spatial pattern of irrigated production is similar to that produced using the single-date algorithm, though irrigated production using the greenness-duration algorithm is
denser in some areas, such as the Magic Valley, and less dense in other areas, such as the northeastern portion of the Plain.

Table 3 presents the percentage change for each accuracy statistic when using the greenness-duration algorithm, calculated relative to the single-date algorithm (Table 2). For the pixel-scale accuracy statistics and the county scale $R^2$, a positive value indicates an improvement in accuracy using the greenness-duration algorithm. For county scale RMSE, a negative value indicates an improvement in accuracy using the greenness-duration algorithm. For example, when using 2002-MODIS-NDVI, the greenness-duration algorithm improves overall accuracy by 10.12% relative to the single-date algorithm. This is equivalent to an increase from an accuracy level of 86.0% (in Table 2) to 94.7%. Accuracy levels for the greenness-duration algorithm are presented in the Appendix in Table A2.

The bottom two rows in Table 3 summarize the average and standard deviation in the percentage change for each column, or accuracy statistic. These summarize the improvement over Table 2 across years, datasets, and indices according to each accuracy statistic. Across pixel-level statistics, the greenness-duration algorithm results in an average improvement over the single-date algorithm of 3.9% for overall accuracy and 8.9% for kappa. For the county level accuracy statistics, the average improvement over the single-date algorithm is 11.3% using $R^2$ and 3.5% using RMSE. The standard deviation for a column captures the variability in the performance of the greenness-duration approach relative to the single-date approach. The change in accuracy is most variable for county level RMSE, which varies from $-58.1\%$ to $+171.4\%$.

Table 3. Percent change in accuracy for greenness-duration algorithm relative to single-date algorithm. Producer’s and user’s accuracies are for the irrigated class.

<table>
<thead>
<tr>
<th>Year</th>
<th>Dataset</th>
<th>Index</th>
<th>Overall Accuracy (%)</th>
<th>Producer's Accuracy (%)</th>
<th>User's Accuracy (%)</th>
<th>Kappa</th>
<th>$R^2$</th>
<th>RMSE (km$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>Landsat</td>
<td>NDVI</td>
<td>3.7</td>
<td>8.2</td>
<td>0.1</td>
<td>8.3</td>
<td>18.6</td>
<td>4.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>3.6</td>
<td>7.9</td>
<td>0.0</td>
<td>7.9</td>
<td>17.1</td>
<td>-7.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>0.7</td>
<td>0.0</td>
<td>1.4</td>
<td>1.4</td>
<td>12.3</td>
<td>-42.0</td>
</tr>
<tr>
<td></td>
<td>MODIS</td>
<td>NDVI</td>
<td>10.1</td>
<td>24.1</td>
<td>0.0</td>
<td>24.1</td>
<td>-3.1</td>
<td>171.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>9.9</td>
<td>23.2</td>
<td>0.0</td>
<td>23.2</td>
<td>6.6</td>
<td>15.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>0.0</td>
<td>-2.8</td>
<td>2.8</td>
<td>0.0</td>
<td>2.6</td>
<td>-19.7</td>
</tr>
<tr>
<td>2007</td>
<td>Landsat</td>
<td>NDVI</td>
<td>-0.7</td>
<td>-1.4</td>
<td>0.0</td>
<td>-1.4</td>
<td>22.8</td>
<td>-35.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>-0.7</td>
<td>-1.4</td>
<td>0.0</td>
<td>-1.4</td>
<td>13.8</td>
<td>-44.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>8.8</td>
<td>19.0</td>
<td>0.3</td>
<td>19.4</td>
<td>19.9</td>
<td>-26.6</td>
</tr>
<tr>
<td></td>
<td>MODIS</td>
<td>NDVI</td>
<td>9.7</td>
<td>20.0</td>
<td>1.7</td>
<td>22.0</td>
<td>1.1</td>
<td>5.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>0.0</td>
<td>-1.4</td>
<td>1.4</td>
<td>0.0</td>
<td>26.3</td>
<td>-58.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>1.4</td>
<td>0.0</td>
<td>2.8</td>
<td>2.9</td>
<td>-2.1</td>
<td>-4.9</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td></td>
<td>3.9</td>
<td>8.0</td>
<td>0.9</td>
<td>8.9</td>
<td>11.3</td>
<td>-3.5</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td></td>
<td>4.3</td>
<td>10.3</td>
<td>1.1</td>
<td>9.9</td>
<td>9.6</td>
<td>57.1</td>
</tr>
</tbody>
</table>

Notes: Percent changes are calculated relative to the accuracy statistic presented in the corresponding cell of Table 2. Accuracy statistic levels for the greenness-duration algorithm are reported in the Appendix in Table A2. Pixel scale significance levels are reported in the Appendix in Tables A4 and A5 for comparisons across compositing algorithms and spectral indices. All differences in county scale performance are significant based on a $z$ score test and a critical level of 0.05.

4.3. Seasonal-Maximum Algorithm

The 2007 Landsat-derived NDMI map using the seasonal-maximum approach is shown in Figure 4C. With respect to location in the SRP, the spatial pattern of irrigated production produced is similar to that using the single-date and greenness-duration algorithms. However, irrigated production in all sub-regions...
of the SRP using this classification algorithm is less dense than it is for either the single-date or greenness-duration algorithms.

Table 4 presents the percentage change for each accuracy statistic when using the seasonal-maximum algorithm, calculated relative to the single-date algorithm (Table 2). For this algorithm, we add the NDMI spectral index value calculated for a nine-cell block surrounding the identification point, denoted NDMI$_{3×3}$. As in Table 3, a positive value for all statistics other than county scale RMSE indicates an improvement in accuracy; a negative value for county scale RMSE indicates an improvement in accuracy. Accuracy levels for the seasonal-maximum algorithm are presented in the Appendix in Table A3.

The average and standard deviations reported in the bottom two rows of Table 4 summarize the relative performance of the seasonal-maximum algorithm across years, datasets, and spectral indices for each accuracy statistic. On average, the improvement in accuracy yielded by the seasonal-maximum algorithm is similar to that attained using the greenness-duration metric. The exception is for county scale RMSE. On average, the seasonal-maximum algorithm outperforms the single-date algorithm by 60.0%. This improvement is much greater than that yielded by the greenness-duration algorithm, 3.5%. In addition, the variability in performance for RMSE is far lower than that of the greenness-duration algorithm. The seasonal-maximum approach improves upon the single-date algorithm for all combinations of years, datasets, and spectral indices, except one (2002 MODIS NDVI) with the change in RMSE ranging from 22.8% to –84.4%. Overall, the Landsat 5 NDMI seasonal maximum method performed best in terms of county scale error (RMSE and $R^2$). Averaged across the two study years, RMSE was 53.8 km$^2$ and $R^2$ 0.978. The performance of Landsat 5 EVI seasonal maximum was only marginally worse with an average RMSE of 66.6 km$^2$ and an $R^2$ of 0.964. All differences in county scale performance are significant based on a z score test and a critical level of 0.05 due to the large number of pixels in the study area. Appendix Tables A4 and A5 present significance values for comparisons across compositing algorithms and spectral indices respectively. Many of the differences between algorithms and indices evident from the county scale validation and from a simple visual inspection do not result in not significant changes in the pixel level accuracy, likely due to limitations in the size and representativeness of this validation dataset. Landsat data generally resulted in higher pixel and county scale accuracies compared to MODIS data. This is likely a result of the coarse resolution of the MODIS data.

**Table 4.** Percent change in accuracy for seasonal-maximum algorithm relative to single-date algorithm. Producer’s and user’s accuracies are for the irrigated class.

<table>
<thead>
<tr>
<th>Year</th>
<th>Dataset</th>
<th>Index</th>
<th>Overall Accuracy (%)</th>
<th>Producer’s Accuracy (%)</th>
<th>User’s Accuracy (%)</th>
<th>Kappa</th>
<th>$R^2$</th>
<th>RMSE (km$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>Landsat</td>
<td>NDVI</td>
<td>7.4</td>
<td>14.8</td>
<td>1.6</td>
<td>16.7</td>
<td>37.5</td>
<td>–62.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>6.5</td>
<td>14.3</td>
<td>0.0</td>
<td>14.3</td>
<td>23.5</td>
<td>–65.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>–1.4</td>
<td>–5.5</td>
<td>2.7</td>
<td>–2.8</td>
<td>16.3</td>
<td>–82.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI$_{3×3}$</td>
<td>0.7</td>
<td>–1.4</td>
<td>2.7</td>
<td>1.4</td>
<td>15.7</td>
<td>–81.0</td>
</tr>
<tr>
<td>2007</td>
<td>MODIS</td>
<td>NDVI</td>
<td>7.8</td>
<td>20.4</td>
<td>–1.5</td>
<td>18.5</td>
<td>–9.1</td>
<td>22.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>6.9</td>
<td>17.9</td>
<td>–1.5</td>
<td>16.1</td>
<td>2.0</td>
<td>–40.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI*</td>
<td>–6.9</td>
<td>–15.5</td>
<td>1.1</td>
<td>–14.5</td>
<td>–53.5</td>
<td>–3.9</td>
</tr>
<tr>
<td>2007</td>
<td>Landsat</td>
<td>NDVI</td>
<td>–1.3</td>
<td>–2.7</td>
<td>0.0</td>
<td>–2.7</td>
<td>30.9</td>
<td>–78.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>–1.3</td>
<td>–2.7</td>
<td>0.0</td>
<td>–2.7</td>
<td>16.5</td>
<td>–81.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>8.0</td>
<td>15.9</td>
<td>1.6</td>
<td>17.7</td>
<td>26.2</td>
<td>–83.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI$_{3×3}$</td>
<td>8.0</td>
<td>15.9</td>
<td>1.6</td>
<td>17.7</td>
<td>26.2</td>
<td>–84.4</td>
</tr>
<tr>
<td>2007</td>
<td>MODIS</td>
<td>NDVI</td>
<td>9.7</td>
<td>20.0</td>
<td>1.7</td>
<td>22.0</td>
<td>6.7</td>
<td>–70.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>0.0</td>
<td>–1.4</td>
<td>1.4</td>
<td>0.0</td>
<td>29.1</td>
<td>–80.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>0.7</td>
<td>–1.4</td>
<td>2.8</td>
<td>1.4</td>
<td>3.1</td>
<td>–49.2</td>
</tr>
<tr>
<td></td>
<td>Average</td>
<td></td>
<td>3.2</td>
<td>6.3</td>
<td>1.0</td>
<td>7.4</td>
<td>12.2</td>
<td>–60.0</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td></td>
<td>4.9</td>
<td>11.3</td>
<td>1.4</td>
<td>10.9</td>
<td>22.1</td>
<td>31.6</td>
</tr>
</tbody>
</table>
Notes: Percent changes are calculated relative to the accuracy statistic presented in the corresponding cell of Table 2. Accuracy statistic levels for the seasonal-maximum algorithm are reported in the Appendix in Table A3. Pixel scale significance levels are reported in the Appendix in Tables A4 and A5 for comparisons across compositing algorithms and spectral indices. All differences in county scale performance are significant based on a z score test and a critical level of 0.05. * The 2002 MODIS NDMI Google composite images contain several large sections of unmasked clouds, lowering the accuracy of the calculated threshold in this instance.

4.4. Spatial Assessment and Non-Irrigated Classification

All three algorithms and indices classify irrigated land with a high degree of accuracy, with overall accuracy values greater than 86% in all cases and 95% in many cases (Table 2, Appendix Tables A2 and A3). This is primarily because of the stark difference in vegetation on irrigated and non-irrigated land during the dry summer growing season. The greatest differences in accuracy occur across different algorithms, as summarized in Tables 3 and 4. To further explore the differences in classification accuracy across the three algorithms, we overlay maps produced using each algorithm for the year-dataset-spectral index combination 2007-Landsat-NDMI. The results are displayed in Figure 5. White areas in the figure indicate parcels for which the three algorithms agree. Purple illustrates parcels for which the season-maximum algorithm (Max) differs from the single-date (SD) and greenness-duration (GD) algorithms. Within the study area, the largest differences in classification between algorithms occur within the riparian zone along the river and in developed areas, which are shaded predominantly in purple. In these cases, the single-date and greenness-duration algorithms tended to misclassify the vegetation as irrigated land. In contrast, the seasonal-maximum approach classifies these pixels as non-irrigated.

Differences in algorithm performance are also evident in the accuracy statistics based on the supplementary land-use validation dataset. Table 5 presents the percentage change in pixel scale overall accuracy when using the greenness-duration and seasonal-maximum algorithms, calculated relative to the single-date algorithm. A positive value in the table indicates an improvement in accuracy relative to the single-date algorithm. The bottom four rows in the table summarize separately the average and standard deviation in the percent change in accuracy for the greenness-duration and seasonal-maximum algorithms relative to the single-date algorithm. The overall accuracy levels for each algorithm are presented in the Appendix in Table A6 and the significance of performance differences between compositing algorithms and spectral indices are presented in Tables A7 and A8, respectively. The seasonal maximum shows significant improvement over both the single date and greenness duration algorithms for every sensor and spectral index, while there were generally no significant differences between the performance of each index. The total percent correctly classified is high across combinations of datasets, indices, and algorithms because the majority of land is in desert (69%), which is correctly classified by all methods with a high degree of accuracy. This is evident in the relatively low average improvement in accuracy yielded by the greenness-duration and seasonal maximum algorithms, of 0.43% and 2.83%, respectively. However, there are important differences in the relative performance of the three algorithms with respect to the classification accuracies for other land-use/land-cover categories. In particular, the seasonal-maximum algorithm substantially outperforms the other two methods in identifying non-agricultural green areas (e.g., riparian areas) and developed areas. This holds across datasets and indices: using the seasonal-maximum algorithm improves the average classification accuracy by 40.81% for non-agricultural green areas and 193.03% for developed areas. This is consistent with the predominantly purple shading for these areas in Figure 5. For these areas, the seasonal-maximum approach also offers a substantial improvement over the greenness-duration algorithm, which improves upon the single-date algorithm by only 1.66% for non-agricultural green vegetation and results in a decline in classification accuracy of 8.93% for developed areas. It is the ability of the seasonal-maximum algorithm to correctly classify these non-irrigated categories that explains
the improvement in the county scale RMSE using the seasonal maximum (Table 4) relative to the single-date and greenness duration algorithms.

Figure 5. A comparison of the seasonal maximum (Max), single date (SD), and greenness duration (GD) algorithm performance using the year-dataset-spectral index combination 2007-Landsat-NDMI. White areas indicate locations where all algorithms agree that the pixel is irrigated; transparent areas are those that all algorithms agree are non-irrigated. Note the misclassification of urban areas from the SD and GD algorithm shown in purple in the inset image of Twin Falls, ID.
Table 5. Percent change in pixel scale overall accuracy for greenness-duration (GD) and seasonal-maximum (Max) algorithms relative to the single-date algorithm using supplementary land-use validation points for 2007.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Index</th>
<th>Algorithm</th>
<th>Non-Irrigated</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODIS</td>
<td>NDVI</td>
<td>GD</td>
<td>Desert</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Non-Ag.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Green Vegetation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Dry Ag.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Developed</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Irrigated Ag.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Total</td>
</tr>
<tr>
<td></td>
<td>Max</td>
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<td></td>
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<td>5.2</td>
</tr>
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<td></td>
<td>-11.8</td>
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<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
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</tr>
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<td></td>
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<td>11.1</td>
</tr>
<tr>
<td></td>
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<td>25.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td>Max</td>
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</tr>
<tr>
<td></td>
<td></td>
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</tr>
<tr>
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Notes: Percent changes are calculated relative to the accuracy statistic for the single-date algorithm. Accuracy statistic levels for all algorithms are reported in the Appendix in Table A4.

5. Discussion

Examination of the multi-temporal trends of NDVI, EVI, and NDMI for our training dataset reveals distinct temporal patterns in elevated index values for irrigated land. The majority of irrigated points exhibit elevated index values following the timing of peak green-up for six composite product cycles (96 days), or approximately three months, prior to declining, likely due to harvest. Other observed trends include: rapidly changing spectra multiple times during the duration of the growing season due to the presence of multi-harvest crops (namely alfalfa); peak response in the late spring and early summer months for spring-planted, irrigated crops; and peak index response during the late summer and early fall months caused by delayed planting. These trends help to explain why the seasonal-maximum algorithm better distinguishes between irrigated agriculture and other areas where vegetation might be green, such as the riparian zone along the Snake River and the urban vegetated environment. Both of these latter scenarios could be considered instances of partial irrigation, characterized by a lesser volume and duration of water use than that for irrigated agriculture. Although the seasonal duration is essentially the same and the contrast between vegetated and non-vegetated land is evident based on all three algorithms, the maximum spectral index value for irrigated land will be greater because vegetation will grow more with additional water use.

The seasonal-maximum algorithm also allows us to accommodate a particular feature of the way that water is allocated to irrigated farms under the state’s system of water rights. Water rights are fulfilled based on the priority (or seniority) of water rights in the region, such that those water rights with an earlier priority date are fulfilled before those with later priority dates. Those fields irrigated with low priority water rights may only have access to water during the beginning of the irrigation season or sporadically thereafter based on available inflows throughout the growing season. In these cases, the seasonal maximum
method is best suited to identify areas that were irrigated at any point during the growing season, as this method is more likely to capture short-duration, elevated spectral index values.

The relatively poor performance of the 2002 MODIS NDMI maximum algorithm is due to unmasked clouds, but it highlights one drawback of using the seasonal maximum method: it is more susceptible to errors due to poor masking. A single image during the year containing unmasked clouds, snow, standing water or other extreme values will be the seasonal maximum for that location, and thus will be carried through to the final composite image. These erroneous values would also alter a seasonal average or median image or a smoothed time series, but its impact would be offset by additional correct values and the magnitude of its effect on the final composite would be smaller.

5.1. Sources of Uncertainty

Some sources of uncertainty should be considered. One potential source of error is the influence of precipitation events that temporarily increase vegetative growth and spectral index values in some regions. In non-irrigated agricultural areas, precipitation during the growing season could cause the index values at these areas to be erroneously classified as irrigated. In addition, rain-fed crops tend to maintain elevated index values longer into the growing season relative to other non-agricultural lands, making discrimination between irrigated and non-irrigated areas subtler and leading to larger irrigated area estimates when compared to the USDA Census.

Selection of training/validation data points for this study is likely another source of error. These datasets are limited and the observation points may not be representative of the region as a whole. This is important to consider when evaluating the pixel level accuracy assessments. All the methods performed relatively well at the pixel scale, so small differences in the performance between methods may only represent classification changes at one or two validation points. The data were developed using NAIP imagery, which is simply a one-time image of the land surface, to locate points that appeared to exhibit irrigated and non-irrigated characteristics. Because these images are snapshot in time and land use can change rapidly, it is possible that irrigation was used at other times during the season. It should also be noted that for the initial point validation (using the symmetrical dataset) only points that could be definitively identified as irrigated or non-irrigated based on the NAIP imagery were included. These points may be easier to classify than the landscape as a whole, and could contribute to the relatively high pixel scale accuracy of all of the methods. Having access to a larger dataset of known land-use points has the potential to significantly improve classification accuracy. Individual-level data on land and water use, such as that collected as part of the USDA Census, are typically private, but improved information on field-scale water use would improve the accuracy with which irrigated lands can be mapped. Finally, inclusion of higher-resolution spatial data quantifying annual precipitation amounts and timing may also improve classification accuracies.

5.2. Future Extensions of This Research

Using the Landsat remote sensing dataset from Google Earth Engine to apply our classification algorithm to the full satellite record can allow for accounting of irrigator decision-making over time. A longer data record would support data-driven studies of the impacts of climate change on land-use decision-making. Additional benefits of using the Landsat remote sensing dataset include the increased spatial resolution from MODIS’s 250-m to 30-m. This allows for a more accurate analysis on the sub-MODIS pixel scale, which reduces errors in small-scale plot classification [38]. For example, multiple irrigated and non-irrigated parcels may reside within one 250-m MODIS pixel, leading to a classification error based upon the intensity of irrigation and the resulting influence on the composited NDVI for that pixel. Research has shown that using data at a finer spatial resolution to map irrigated land improves classification accuracy [5]. The downside with Landsat, however, is that the temporal resolution increases to
approximately 16 days between each image capture. If insufficient cloud-free images are available, it is challenging to accurately describe the trajectory of NDMI over the growing season and difficult to implement the greenness-duration or seasonal-maximum algorithms. Researchers may thus be forced to accept a tradeoff between spatial resolution and classification accuracy. The decision of which dataset and algorithm(s) to use will depend on the particular research question at hand and the spatial scale at which decision-making processes operate.

Limiting the study region to areas suitable for agriculture is also an important component of this analysis. Forested regions and riparian zones show elevated NDVI and other spectral index values, similar to irrigated areas, meaning they appear as though they are irrigated. Because the influence of riparian zones is limited in our study region, our main focus is on masking out forested areas. The presence of forests poses a significant problem when attempting to quantify irrigated land use at the county scale, likely resulting in an overestimation of irrigated land use. There appear to be distinct patterns in the NDVI curves including the timing of green-up, the slope of the decline in greenness during the growing season, and the timing of rapid NDVI drop-off near the end of the year, likely attributable to the presence of snow or defoliation of undergrowth in inter-canopy spaces. With further exploration of these patterns, a method for removing these regions could be developed.

Lastly, we must discuss the broader applications of our classification method for mapping other semi-arid to arid regions. The developed method relies on region specific training data to calculate each threshold. Since the thresholds are data driven, this method is likely applicable to other regions once a training dataset has been created and could be applied to other types of smoothed time series or composites. Our methods are directly applicable to areas with a “summer dry” climate because they fundamentally rely on a lack of available water for plant consumption during the summer months to identify locations that receive supplemental irrigation water. Because of this assumption, our approaches will be less accurate in areas with “summer wet” climates. It is possible to apply our method to these regions by adjusting the timing and length of the observation window. The required change to the observation period would depend on the timing and length of the growing season along with the timing and magnitude of precipitation. If there is a significant amount of time in which precipitation is low and temperatures are high during the growing season, this method could be applied to map irrigated agricultural land use in areas with “monsoon-driven” semi-arid to arid climates.

6. Conclusions

At the regional scale, we demonstrate that the top performing algorithm in terms of classification accuracy is the seasonal-maximum algorithm, primarily due to its out-performance of the other approaches in appropriately classifying lands in riparian and developed areas. While the most accurate method in terms of county scale RMSE and R² is the seasonal maximum of Landsat 5 NDMI, it only marginally outperforms the next best method (Landsat 5, EVI seasonal maximum). Differences in classification accuracy between spectral indices and sensors are fairly modest, but larger differences can be seen between image compositing algorithms. The seasonal maximum algorithm reduces county scale RMSE by an average of 60% over the single-date algorithm, and yields a consistent improvement in classification accuracy across virtually all years and spectral indices. The improved ability of the seasonal-maximum algorithm to classify irrigated and non-irrigated lands at a regional scale is a critical tool for water managers that can support improved predictions of changes in competition for increasingly scarce water resources and provide the information needed to support more efficient water management techniques [5].

Using the seasonal-maximum of spectral vegetation indices, we develop an efficient and computationally inexpensive method for mapping irrigated land use that is broadly applicable to “summer dry” Mediterranean style semi-arid to arid climates. Results show an average percent error reduction when compared to the single-date algorithm of Ozdogan et al. [5]. This is encouraging, given the variability across
our study region in terms of topography, precipitation, and temperatures, which represents a significant difference between our analysis and the relatively homogeneous study area in Turkey evaluated by Ozdogan et al. [5].

**Supplementary Materials:** A Google Earth file (kmz) containing the training and validation datasets used in this analysis is available online at: (TBD-uploaded as Supplementary Material.) The code used in this analysis is available online at: https://github.com/ericwchance/Irrigation_Extent/.

**Acknowledgments:** Support for this study is provided by the NASA Land Cover/Land Use Change Program under award NNX14AH15G, a Junior Faculty Award from the Virginia Tech Institute for Critical Technology and Applied Science, and the McIntire-Stennis Cooperative Forestry Research Program.

**Author Contributions:** All authors took part in the conception and designed the study. E.C. performed the experiments and analyzed the data. E.C. and B.D. drafted the manuscript, which was revised by K.C. and V.T. K.C., V.T. and A.F. managed this research.

**Conflicts of Interest:** The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

**Appendix A**

**Table A1.** Threshold values for each year and algorithm. Producer’s and user’s accuracies are for the irrigated class.

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</table>

Notes: Some of the data products used have values scaled by 10,000 so the resulting thresholds are also scaled. Single date methods used 16 and 32 day composites, dates listed are the starting date of each composite (month/day).

**Table A2.** Greenness-duration algorithm classification accuracy. Producer’s and user’s accuracies are for the irrigated class.

<table>
<thead>
<tr>
<th>Year</th>
<th>Dataset</th>
<th>Index</th>
<th>Overall Accuracy (%)</th>
<th>Producer’s Accuracy (%)</th>
<th>User’s Accuracy (%)</th>
<th>Kappa</th>
<th>R²</th>
<th>RMSE (km²)</th>
</tr>
</thead>
</table>

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<table>
<thead>
<tr>
<th></th>
<th>NDVI</th>
<th>EVI</th>
<th>NDMI</th>
<th></th>
<th>NDVI</th>
<th>EVI</th>
<th>NDMI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Landsat 2002</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>MODIS 2002</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI</td>
<td>93.3</td>
<td>91.3</td>
<td>98.5</td>
<td>EVI</td>
<td>95.3</td>
<td>90.7</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI</td>
<td>94.7</td>
<td>89.3</td>
<td>100.0</td>
<td>EVI</td>
<td>96.0</td>
<td>92.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>

| **Landsat 2007** | | | | **MODIS 2007** | | | | |
| NDVI | 98.7 | 97.3 | 100.0 | EVI | 98.7 | 97.3 | 100.0 | NDMI | 99.3 | 100.0 | 98.7 |
|       |       |       |   |       |   |       |   |       |       |       |   |       |
| NDVI | 98.0 | 96.0 | 100.0 | EVI | 98.7 | 97.3 | 100.0 | NDMI | 97.3 | 94.7 | 100.0 |

<table>
<thead>
<tr>
<th></th>
<th>NDVI</th>
<th>EVI</th>
<th>NDMI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.867</td>
<td>0.802</td>
<td>295</td>
</tr>
<tr>
<td>MODIS</td>
<td>0.907</td>
<td>0.903</td>
<td>220</td>
</tr>
<tr>
<td></td>
<td>0.960</td>
<td>0.941</td>
<td>203</td>
</tr>
<tr>
<td></td>
<td>0.893</td>
<td>0.865</td>
<td>319</td>
</tr>
<tr>
<td>MODIS</td>
<td>0.920</td>
<td>0.970</td>
<td>184</td>
</tr>
<tr>
<td></td>
<td>0.920</td>
<td>0.944</td>
<td>239</td>
</tr>
<tr>
<td></td>
<td>0.973</td>
<td>0.900</td>
<td>199</td>
</tr>
<tr>
<td>MODIS</td>
<td>0.973</td>
<td>0.954</td>
<td>148</td>
</tr>
<tr>
<td></td>
<td>0.987</td>
<td>0.932</td>
<td>213</td>
</tr>
<tr>
<td></td>
<td>0.960</td>
<td>0.882</td>
<td>315</td>
</tr>
<tr>
<td>MODIS</td>
<td>0.973</td>
<td>0.955</td>
<td>205</td>
</tr>
<tr>
<td></td>
<td>0.947</td>
<td>0.928</td>
<td>243</td>
</tr>
</tbody>
</table>
Figure A1. The 2007 irrigated areas classified using MODIS NDMI for the three algorithms: (A) single date algorithm; (B) greenness duration algorithm; and (C) seasonal-maximum algorithm. Non-irrigated areas are shown in white, irrigated areas are green and masked areas outside the study region are grey.
Table A3. Seasonal-maximum algorithm classification accuracy. Producer’s and user’s accuracies are for the irrigated class.

<table>
<thead>
<tr>
<th>Year</th>
<th>Dataset</th>
<th>Index</th>
<th>Pixel Scale</th>
<th>County Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Overall Accuracy (%)</td>
<td>Producer’s Accuracy (%)</td>
</tr>
<tr>
<td>2002</td>
<td>Landsat</td>
<td>NDVI</td>
<td>96.7</td>
<td>93.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>98.0</td>
<td>96.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>96.0</td>
<td>92.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI₃×3</td>
<td>98.0</td>
<td>96.0</td>
</tr>
<tr>
<td></td>
<td>MODIS</td>
<td>NDVI</td>
<td>92.7</td>
<td>86.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>93.3</td>
<td>88.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>89.3</td>
<td>80.0</td>
</tr>
<tr>
<td></td>
<td>MODIS</td>
<td>NDVI</td>
<td>98.0</td>
<td>96.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>98.0</td>
<td>96.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>98.7</td>
<td>97.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI₃×3</td>
<td>98.7</td>
<td>97.3</td>
</tr>
<tr>
<td>2007</td>
<td>Landsat</td>
<td>NDVI</td>
<td>98.0</td>
<td>96.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>98.7</td>
<td>97.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>96.7</td>
<td>93.3</td>
</tr>
</tbody>
</table>

* The 2002 MODIS NDMI Google composite images contain several large sections of unmasked clouds, lowering the accuracy of the calculated threshold in this instance.

Table A4. p values for McNemar test of significance in difference between image compositing algorithms for the pixel scale classification accuracy. Values less than 0.05 are highlighted in light grey and those less than 0.01 are highlighted in dark grey.

<table>
<thead>
<tr>
<th>Year</th>
<th>Dataset</th>
<th>Index</th>
<th>Single Date V. G.D.</th>
<th>Max. V. G.D.</th>
<th>Max. V. Single Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>Landsat</td>
<td>NDVI</td>
<td>0.267</td>
<td>0.546</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>0.228</td>
<td>0.221</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>1.000</td>
<td>0.131</td>
<td>0.077</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI₃×3</td>
<td>0.480</td>
<td>0.450</td>
<td></td>
</tr>
<tr>
<td></td>
<td>MODIS</td>
<td>NDVI</td>
<td>0.004</td>
<td>1.000</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>0.009</td>
<td>0.752</td>
<td>0.029</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>0.221</td>
<td>0.043</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>MODIS</td>
<td>NDVI</td>
<td>1.000</td>
<td>1.000</td>
<td>0.617</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>1.000</td>
<td>1.000</td>
<td>0.617</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>0.001</td>
<td>0.248</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI₃×3</td>
<td>0.248</td>
<td>0.027</td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td>Landsat</td>
<td>NDVI</td>
<td>0.006</td>
<td>0.480</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td></td>
<td>EVI</td>
<td>0.617</td>
<td>0.480</td>
<td>0.617</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NDMI</td>
<td>0.683</td>
<td>1.000</td>
<td>0.371</td>
</tr>
</tbody>
</table>

* The 2002 MODIS NDMI Google composite images contain several large sections of unmasked clouds, lowering the accuracy of the calculated threshold in this instance.

Table A5. p values for McNemar test of significance in difference between spectral indices for the pixel scale classification accuracy. Values less than 0.05 are highlighted in light grey and those less than 0.01 are highlighted in dark grey.

<table>
<thead>
<tr>
<th>Year</th>
<th>Dataset</th>
<th>Index</th>
<th>NDVI V. EVI</th>
<th>NDMI V. EVI</th>
<th>NDMI V. NDVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>Landsat</td>
<td>S.D.</td>
<td>1.000</td>
<td>0.022</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>G.D.</td>
<td>1.000</td>
<td>0.041</td>
<td>0.046</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Max.</td>
<td>0.480</td>
<td>0.450</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>MODIS</td>
<td>S.D.</td>
<td>0.752</td>
<td>0.001</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td></td>
<td>G.D.</td>
<td>0.752</td>
<td>0.752</td>
<td>0.752</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Max.</td>
<td>1.000</td>
<td>0.211</td>
<td>0.359</td>
</tr>
</tbody>
</table>
Table A6. Classification accuracy of supplementary land-use validation points for 2007.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Index</th>
<th>Algorithm</th>
<th>Percent Correctly Classified</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Non-Irrigated</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Desert</td>
</tr>
<tr>
<td>NDVI</td>
<td>SD</td>
<td>97.7</td>
<td>70.8</td>
</tr>
<tr>
<td></td>
<td>GD</td>
<td>97.3</td>
<td>54.2</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>99.5</td>
<td>95.8</td>
</tr>
<tr>
<td>MODIS</td>
<td>EVI</td>
<td>99.1</td>
<td>81.7</td>
</tr>
<tr>
<td></td>
<td>GD</td>
<td>93.2</td>
<td>66.7</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>NDVI</td>
<td>SD</td>
<td>95.5</td>
<td>62.5</td>
</tr>
<tr>
<td></td>
<td>GD</td>
<td>97.7</td>
<td>70.8</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>99.5</td>
<td>95.8</td>
</tr>
<tr>
<td>Landsat</td>
<td>EVI</td>
<td>96.8</td>
<td>66.7</td>
</tr>
<tr>
<td></td>
<td>GD</td>
<td>99.5</td>
<td>79.2</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>NDMI</td>
<td>SD</td>
<td>95.9</td>
<td>58.3</td>
</tr>
<tr>
<td></td>
<td>GD</td>
<td>99.5</td>
<td>75.0</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>100.0</td>
<td>95.8</td>
</tr>
<tr>
<td></td>
<td>Max&gt;3</td>
<td>100.0</td>
<td>95.8</td>
</tr>
<tr>
<td>Total Samples</td>
<td>220</td>
<td>24</td>
<td>12</td>
</tr>
</tbody>
</table>

Table A7. p values for McNemar test of significance in difference between image compositing algorithms for the classification accuracy of supplementary land-use validation points for 2007. Values less than 0.05 are highlighted in light grey and those less than 0.01 are highlighted in dark grey.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Index</th>
<th>Method</th>
<th>NDVI V. EVI</th>
<th>NDMI V. EVI</th>
<th>NDMI V. NDVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat</td>
<td>SD</td>
<td>0.724</td>
<td>0.114</td>
<td>0.211</td>
<td></td>
</tr>
<tr>
<td></td>
<td>G.D.</td>
<td>0.343</td>
<td>0.343</td>
<td>0.803</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Max.</td>
<td>0.480</td>
<td>0.134</td>
<td>0.617</td>
<td></td>
</tr>
<tr>
<td>MODIS</td>
<td>SD</td>
<td>0.018</td>
<td>0.000</td>
<td>0.081</td>
<td></td>
</tr>
<tr>
<td></td>
<td>G.D.</td>
<td>0.000</td>
<td>0.386</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Max.</td>
<td>0.371</td>
<td>0.579</td>
<td>0.803</td>
<td></td>
</tr>
</tbody>
</table>

Table A8. p values for McNemar test of significance in difference between spectral indices for the classification accuracy of supplementary land-use validation points for 2007. Values less than 0.05 are highlighted in light grey and those less than 0.01 are highlighted in dark grey.
References


31. DAAC, L., *Land Processes Distributed Active Archive Center* 2014, USGS and NASA.


Chapter 3. Time series analysis of Irrigation extent in Idaho’s Snake River Basin

3.1. Introduction

Water availability is a major factor in agricultural decision making and the resulting economic outcomes. Ironically, while water is vital to the production of any crop, much of the nation’s most productive croplands are located in the arid or semi-arid west where rainfall is limited during the growing season, and irrigation either from surface or groundwater is necessary for most crops to grow. Increasing competition for limited water supplies from agricultural expansion, urban, industrial and environmental protection uses have increased the demand on this finite resource, meanwhile climate change has the potential to further limit water supplies (Cobourn, Xu, Lowe, & Mooney, 2013; Elliott et al., 2014; Winter et al., 2017).

Remote sensing data provide an accurate and efficient means of evaluating changes on the earth’s surface across areas which are too large to feasibly survey on the ground. In regions where there is limited precipitation during the growing season, anomalies in plant greenness and water content can generally be attributed to irrigation (Ozdogan, Woodcock, Salvucci, & Demir, 2006). Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Moisture Index (NDMI) provide computationally efficient means of measuring greenness and water content, and allow for straightforward mapping of areas with and without water applications (Biggs et al., 2006; Draeger, 1977; Myneni, Hall, Sellers, & Marshak, 1995; Nicholson, Davenport, & Malo, 1990; Ozdogan, Yang, Allez, & Cervantes, 2010).

An understanding of irrigator responses to changes in water availability provides vital information necessary to develop efficient water management policies. This is especially important in the face of potentially increasing water shortages and water supply destabilization due to climate change. In this study, I examine the changes in the extent of irrigated lands in Idaho’s Snake River Plain (SPR) between 1984 and 2016. Using a binary threshold on the seasonal maximum of NDMI for Landsat 5-8 data I classify irrigated and non-irrigated lands within the region for each year. This time series is used to examine the impacts of climate data and water rights characteristics on changes in irrigation extent and intensity over time.

3.2. Study Area

3.2.1. Geographic and Climatic Characteristics

The Snake River Plain (SRP), underlain by the Snake Plain Aquifer (SPA) spans most of southern Idaho and is home to most of the state’s population and its most productive farmlands. Approximately 500 m east to west, the region has a Mediterranean style arid to semi-arid climate. Summers are typically dry, and as such agriculture in the regions relies heavily on irrigation from surface waters and from the underlying Snake Plain Aquifer. The Aquifer is divided into two largely independent portions the Eastern Snake Plain Aquifer, which discharges into the Snake River in the Thousand Springs area, and the western portion spanning the remainder of the SPA. An overview map of the SRP is shown in Figure 3-1. Climate varies substantially across the plain largely as a result of a west to east increase in elevation, varying from approximately 680m above mean sea level in the west to 1680m in the east (USGS, 2015). Within the SRP, the highest temperature and lowest precipitation amounts can be found in the west which has a maximum mean annual temperature of 13°C and only receives about 25cm per year of rain. Higher precipitation amounts can be found in the east, up to approximately 35 cm
per year, most of which falls during the winter months (Ruffner & Bair, 1985). The plain is surrounded by mountains in excess of 2800m in elevation, which receive substantially more precipitation throughout the year, and snowpack from these mountains is the source of much of the water used for irrigation within the plain which makes the region especially vulnerable to the impacts of climate change (Karl, 2009). Snowpack in the region are expected to decline, primarily as a result of a shift in precipitation from snow to rain as a result of higher temperatures (Dettinger, Knowles, & Cayan, 2015; Knowles, Dettinger, & Cayan, 2006). In fact, some shifts towards earlier spring snowmelt have already been observed, and it is thought that in future years there will be increasing variability in the timing and magnitude of snowmelt runoff (Barnett et al., 2008; Kormos, Luce, Wenger, & Berghuijs, 2016; Kunkel & Pierce, 2010; Mote, Hamlet, Clark, & Lettenmaier, 2005).

Figure 3-1. Overview map of the Snake River plain. The eastern portion of the plain is shown in yellow, and the western portion in pink.

In the SRP, the availability of irrigation water is a primary driver of agricultural productivity, land values, and farmers’ land-use decisions. Within the SRP a large portion of the land with soils suitable for cultivated agriculture are not being used (USDA, 1995). Rather, the extent of agriculture in this arid region is largely defined by water rights. Idaho has the third highest total water withdrawal volume of any state and ranks first in terms of withdrawal volume per capita (USGS, 2016). The vast majority (over 98%) of all water withdrawn in in the state is in counties within the SRP, the majority of that which (85.6%) is used for irrigation (Kenny et
Irrigators rely on groundwater and reservoir storage to irrigate during the summer months when stream flows would naturally be declining. Increased variability in water availability due to changes in water snow storage will introduce uncertainty into agricultural production and likely influence land-use patterns, and the region’s economy, hydrology, and ecology (Hansen, Lowe, & Xu, 2014).

The primary crops grown in the SRP are spring and winter wheat, alfalfa, barley, corn, potato and sugar beet. Only approximately 30% of the plain is in agriculture, undeveloped lands are predominantly covered in shrub and scrub, transitioning to pine forests in the higher elevation areas of the surrounding mountains (Fry et al., 2011).

3.2.2. Water Allocation Within the Snake Plain

Water allocation in the SPR, like most western states is based on the prior appropriation doctrine which is often explained as “first in time, first in right”. Water rights allocate specific quantities of water to irrigators, and the date the water right was issued (referred to as the priority date) dictates its hierarchical rank, where those with older rights have priority over newer ones. Under this policy the Idaho Department of Water Resources (IDWR) monitors surface water availability and sets a priority date cutoff for each surface water diversion point and groundwater region in the case of a shortage. Those with rights older than the cutoff date receive their full water allocation, and rights newer than the cutoff date receive none. A notable difference between Idaho’s water allocation laws and those of most other Western states is that in Idaho water rights are tied to specific parcels of land. This potentially poses an additional burden to water rights trading and the implementation of markets to facilitate such trading, but it allows for more straightforward geospatial analysis of water rights and water use (Plummer, Rupert, Busenberg, & Schlosser, 2000). Additionally, since most irrigators have access to their own, largely unmonitored groundwater wells, water rights are largely regulated in terms of the spatial extent of irrigation, rather than the intensity of water application, so accurate mapping of irrigation extent is especially important in this region.

A number of prior studies have been completed examining the interplay between water use and water rights in this region. Several of these studies use economic models to assess the impacts of water allocation characteristics on farmers in the ESPA. Xu et al. (2014) examined economic outcomes of irrigators and the impacts of their specific water rights. The study found that farmers respond to seasonal and long term changes in water supply as well as seasonal water supply forecasts based on the priority date of their water rights. Older, more secure rights were associated with elevated crop revenue and less secure rights were associated with lower revenues. Responses to seasonal water supply forecasts were varied based on water rights. Additionally, weak influences of market forces but strong institutional impacts were observed. In this study, the authors did not identify changes in irrigation technology or examine surface-groundwater interactions (Wenchao Xu, 2014; W. Xu, Lowe, & Zhang, 2014).

Xu et al (2015) expounded on previous studies, focusing specifically on irrigation extent, finding a 1% increase in a farmer’s irrigated area lead to a $18/hectare increase in crop revenue. Both crop revenue and irrigation extent are impacted by long term water stress. Xu predicts that under Idaho’s current water management structure, junior water rights holders will leave the market due to persistent water shortages causing average irrigation extent and revenues to increase (Wenchao Xu & Li, 2015).
3.3. Methods

This study builds on the prior work of Chance et al. (2017), which compared several image classification methods and spectral indices to identify irrigated lands in the Snake River Plain of Idaho. Results of the prior study suggested that a binary threshold on Landsat 5 Normalized Difference Moisture Index (NDMI) seasonal maximums produced the most consistently accurate separation of irrigated versus non-irrigated land (Chance, Cobourn, Thomas, Dawson, & Flores, 2017). In this work, I applied our algorithm to Landsat time series from 1984-2016 to assess the temporal dynamics of irrigation in the region. To create the time series, a threshold is determined for each year to distinguish between irrigated and non-irrigated pixels. The thresholds were determined based on a constant training dataset of known irrigated and non-irrigated points, to which adjustments were made to correct for changes in irrigation practices at those points.

The analysis was completed in Google Earth Engine API. The Landsat time series consists of imagery from 1984-2016, using Landsat 5 (1984-2011), Landsat 7 (2012), and Landsat 8 (2013-2016) all of which is at a 30-m resolution. I used surface reflectance data sets, and performed cloud masking based on Fmask (Zhu, Wang, & Woodcock, 2015) values provided with each dataset. Additionally, the 2011 National Landover Database (NLCD) was used to mask out water, barren, forest and scrub lands in some of the output maps.

3.3.1. Image Classification

A binary image classification was performed based on the seasonal maximum NDMI value for each pixel compared to a threshold value. NDMI, also referred to as the Normalized Difference Water Index (NDWI), is defined as:

\[
\text{NDMI} = \frac{\rho_{\text{nir}} - \rho_{\text{swir1}}}{\rho_{\text{nir}} + \rho_{\text{swir1}}}
\]

where \(\rho_{\text{swir1}}\) represents short wave infrared (1.55 - 1.75\(\mu\)m) reflectance (Gao, 1996). For purposes of this study growing season is defined as April 1 through October 31.

To determine the threshold, a training dataset of 404 known land-use points was developed using manual interpretation of the National Agriculture Imagery Product (NAIP), which consists of high resolution aerial photographs. Approximately 10 irrigated and 10 non-irrigated points were selected within each of the 21 counties in the Snake River Plain. In our study region, NAIP images are available for the 2003, 2004, 2006, and 2009 growing seasons, and points were selected that were either always irrigated or always not irrigated for the seasons with imagery available. At each sample point nine pixel values are taken (a three by three square), and are used to calculate the threshold values. To account for irrigation infrastructure, farm equipment and other anomalies, any pixel values outside two standard deviations of the mean NDMI within each nine-pixel square are removed.

The threshold value for each year is calculated by identifying the point at which classifying the points as irrigated or non-irrigated is equal, based on two separate non-parametric kernel density function distributions for the irrigated and non-irrigated values. Distributions for the irrigated and non-irrigated control point NDMI maximum values were calculated for each year using the Matlab’s \textit{kdensity} function which uses a frequency of 1/100\textsuperscript{th} of the range of the data (Bowman & Azzalini, 1997). A threshold was selected where the probability of classifying a point as irrigated or non-irrigated was equal, this represents the point where the two kernel density functions intersect.
3.3.2. Control Point Adjustments

To avoid confusion, the value used for image classification will be referred to as the threshold or classification threshold, and the values used for dropping points will be referred to as a cutoff. Thresholds were derived for each year based on the values found at each point in the training data set. I selected only control points that had a consistent land-use and irrigation status over time, confirmed through interpretation of the NAIP imagery, however since the NAIP imagery did not extend back to 1984, the irrigation status was not definitely known for each year. Some points were removed if it appeared that their irrigation characteristics were different in the earlier growing seasons (i.e., 1984-2002). I tested several methods to identify the points where irrigation status was different in the earlier period, with the goal of identifying a method that removes misclassified points while still retaining as much of the inherent variability of each distribution. I evaluated the methods based on several criteria: the number of points dropped each year should be minimized and decreasing over time but the resulting yearly thresholds and irrigated areas should be minimally correlated with time or the number of points dropped. Removing these incorrectly classified points was especially important because they are located on the tails of the two fitted distributions causing them to have an outsized effect on the shape of each distribution, thus altering the point at which they intersect (the classification threshold).

I test three conventional methods for identifying and dropping outliers in univariate datasets, a z-score of 3, a z-score of 2 and a modified z-score of 3.5. The z-score is essentially a multiplier of the standard deviation. So for the z-score of 3, points outside of a 3 standard deviation range from the mean were dropped and for the z-score of 2 those outside a 2 standard deviation range were dropped (Ben-Gal, 2005; Hodge & Austin, 2004; Seo, 2006). In this case I am only dropping irrigated points that are below the two or three standard deviation cutoff and non-irrigated points in excess of each cutoff. The modified z-score is a measure of deviation from the median, rather than a measure of deviation from the mean as the standard z-score, and is thus less susceptible to skewing as a result of extreme values and outliers. The modified z-score is defined as:

\[ M_i = \frac{0.6745(x_i - \bar{x})}{\text{median}(|x_i - \bar{x}|)} \]  

(3.2)

Where \( M_i \) is the modified z-score for value \( x_i \) and \( \bar{x} \) denotes the median of the population. It has been suggested that \( |M_i| < 3.5 \) is an appropriate cutoff for identifying outliers (Iglewicz & Hoaglin, 1993).

A subtle but important distinction can be made between the methods listed above and the next two methods: those above aim to drop outliers, while those discussed below aim to drop misclassified points. The conventional methods of dropping outliers discussed above performed poorly for this dataset because of the large number of misclassified points in the older years skewed each of the statistics used. As one moves back in time more misclassified points were included so the center (mean or median) of the irrigated and non-irrigated distributions shifted towards each other while the standard deviation and median absolute deviation of each distribution got larger. This made differentiating between the two categories and identifying miscategorized points more difficult (see Figure 3-2).
Two additional methods were examined that aim to drop misclassified values rather than simply dropping outliers. The first, referred to as the one standard deviation variable cutoff method, drops points within one standard deviation of the mean of the other category. For instance, irrigated points that were within one standard deviation of the mean of the non-irrigated points would be dropped, and vice versa. Essentially this method aims to drop points that have likely shifted into the wrong category as one moves back in time. However, this method is still impacted by the shifts in the standard deviations and means over time as a result of there being more misclassified points in the older datasets. The last method tested, and the one selected for use in the time series analysis is referred to as the one standard deviation constant cutoff method. This method is similar to the variable cutoff method discussed above, but instead of calculating cutoff values for each year, constant cutoff values were used for every year. Again I dropped points that were within one standard deviation of the mean of the opposite distribution, however in this case I calculate cutoff values based on the period where NAIP imagery was available for validation (2002-2011), and use these cutoff values for the entire time series. This method has the clear advantage of fully removing the influence of miscategorized points in the older dataset in determining which points are dropped.

Misclassified points were identified using a single cutoff of one standard deviation from the mean of the opposite class, based on an average mean and standard deviation for irrigated and non-irrigated points for the time period with effective training data (2002-2011), so irrigated NDMI max values below 0.163 were dropped, as were non-irrigated values above 0.460 dropped. Figure 3-2 provides a visual summary of this point dropping method.

**Figure 3-2.** Diagram of the one standard deviation constant cutoff point dropping method. Probability density functions for irrigated and non-irrigated NDMI value distributions are shown, as well as the one standard deviation cutoff, and the resulting classification threshold. The inclusion of misclassified points in the older datasets causes the distributions to shift towards each other. The final threshold would actually be slightly different than what is indicated here, but it would still be at the point where the two distributions intersect. It would be in a different location because the shape of each distribution would shift once the points in the shaded regions are dropped.
3.3.3. Time Series Development

Seasonal variation in irrigation extent can be examined by comparing the extent of irrigation each year, however longer term changes may be overshadowed by seasonal variations such as crop rotation. Two to three-year crop rotations are common in Idaho, but four to five year rotations are often recommended to increase per hectare revenues and minimize pest and disease risks (Myers, McIntosh, Patterson, Taylor, & Hopkins, 2008). In order to evaluate longer-term changes in irrigation extent, areas that have been irrigated any time in the preceding 5 years were identified for each year. The 2011 was used in place of the 2012 layer for this process to avoid erroneous values caused by the Landsat 7 scan line corrector failure. Since this methodology combines multiple years, false positives are potentially more prevalent, so additional masking was performed for the change layers using the 2006 National Land Cover Database (NLCD) (Fry et al., 2011). Water, barren lands (the study area contains large areas of exposed lava that are highly reflective), forest and scrublands were masked. Summary statistics were calculated by county, based on the 21 counties containing the Snake Plain Aquifer, with large forested areas delineated and masked out by hand.

3.3.4. Examination of Factors Contributing to Change

Several other datasets were incorporated into this study in an attempt to examine the impact of various factors potentially contributing to changes in NDMI or changes in irrigation extent across time. Two precipitation datasets were used as a proxy for water availability. The first is a gridded (approximately 4 km resolution) precipitation water year (beginning and ending October 1) totals produced by the National Weather Service. This data product is based on radar extrapolations, corrected using language measurements, and is available from 2006-2016 (NOAA & NWS, 2016). Sums of all cell values were taken (missing values were replaced with the average value for that water year) and multiplied by the scale and area to give a total precipitation volume for the upper Snake River/East Snake River Plain Aquifer Watershed (Laitta, Legleiter, & Hanson, 2004). Longer term precipitation data for the entire study period was examined for a single, centrally located rain gauge located in Jerome, ID. Total precipitation amounts were calculated for each water year (beginning and ending October 1) (NOAA, 2016). It is assumed that groundwater is relatively uniformly available year to year, and thus the primary focus is on surface water availability.

Irrigation extent measurements were applied to individual water rights within the Eastern Snake Plain Aquifer (ESPA). I apply both the long term change layer, as well as the individual irrigation extent layers for each year to all the water rights, providing two end products: areas added to and removed from irrigation in each water right over the long term and the extent of irrigation each year within each water right. The Idaho Department of Water Resources maintains and regulates the state’s spatially explicit water rights (IDWR, 2015). Because most irrigators have multiple water rights with different characteristics (perhaps different priority dates, groundwater and surface water sources, etc.) and potentially different spatial extents, each water right was broken down into “stacks”. Each stack contains a unique combination of overlapping water rights. These stacks were determined using ArcGIS. The water rights layer was intersected with itself, returning all internal boundaries and all regions with at least two rights. Areas with only one right were identified by erasing the original water rights with the previously created intersected rights. The two layers (those with two or more rights and those with a single right) were then merged together to create a single layer, where each stack was given a unique identification number. Because of alignment errors in the original water rights...
dataset, this process created many slivers of rights where boundaries of overlapping rights did not perfectly align. These slivers were removed by removing all shapes that were less than 2,000 square meters, and those where the ratio of perimeter to area greater than 10. Rights were overlapped with the long term change map discussed above and cell counts within each right were used to calculate percent added to and removed from agriculture for the period of 1988-2016. Rights stacks with less than 5 overlapping cells were dropped from this analysis.

In addition to examining irrigation extent, I also use mean yearly and monthly NMDI values as a proxy to estimate irrigation intensity (assuming that precipitation has a nominal effect on NMDI in irrigated areas). For each year, mean NDMI cell values of irrigated and non-irrigated pixels were separately applied to each water right stack in order to examine policy impacts on irrigation intensity.

3.3.5. Regression Analysis of Evapotranspiration and Crop Data

I also examined several existing data sources relevant to SRP water use. I used simple liner regression to examine the impact of various factors that potentially drive water use and farm revenue. Mapping Evapotranspiration using high Resolution and Internalized Calibration (METRIC), is a remotely sensed measure of evapotranspiration (an energy balance model) developed specifically for this region by researchers at the University of Idaho and Idaho Department of Water Resources will be used (Allen, Tasumi, Morse, & Trezza, 2005). It is derived primarily on Landsat 5 Thermal and infrared bands, and it is available on a growing season or monthly basis for 1984-2011 at a 30m resolution. The METRIC data was used to estimate total seasonal water use in each irrigator of sub irrigator unit.

The Cropland Data Layer (CDL), produced by USDA was used to determine crop type (USDA, 2015). The CDL is only available for Idaho for 2008-2014. It is available at a 30m resolution (with the exception of the 2009 dataset which is available at a 56m resolution.) This dataset contains several hundred crop types, but for this study, it was generalized into the 10 primary crop types grown in the ESPA (Table 3-1).

<table>
<thead>
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<th>Reclassified Value</th>
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<th>CDL Name</th>
<th>CDL Values</th>
</tr>
</thead>
<tbody>
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<td>Alfalfa</td>
<td>36</td>
</tr>
<tr>
<td>2</td>
<td>Other Hay/Non Alfalfa</td>
<td>Other Hay/Non Alfalfa</td>
<td>37</td>
</tr>
<tr>
<td>3</td>
<td>Barley</td>
<td>Barley</td>
<td>21</td>
</tr>
<tr>
<td>4</td>
<td>Spring Wheat</td>
<td>Spring Wheat</td>
<td>23</td>
</tr>
<tr>
<td>5</td>
<td>Winter Wheat</td>
<td>Winter Wheat</td>
<td>24</td>
</tr>
<tr>
<td>6</td>
<td>Potatoes</td>
<td>Potatoes</td>
<td>43</td>
</tr>
<tr>
<td>7</td>
<td>Sugar beets</td>
<td>Sugar beets</td>
<td>41</td>
</tr>
<tr>
<td>8</td>
<td>Corn</td>
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<td>1, 12, 13</td>
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<tr>
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<td></td>
<td></td>
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</tr>
<tr>
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<td>Other Ag. (Many)</td>
<td>(Many)</td>
<td>35, 38-41, 42, 44-110, 196-254</td>
</tr>
<tr>
<td>10</td>
<td>Other Non Ag.</td>
<td>Developed, Forest, Water, Shrubs</td>
<td>0, 255, 111-195</td>
</tr>
</tbody>
</table>
SSURGO soils data, produced by the USDA was used, because it includes expected crop yields by crop type for each soil type (USDA, 1995). This data is reported in vector form and is available for most of the soil districts in the ESPA. Expected yields are average values, assuming water and fertilizer application rates that are typical for each crop. Mapped soil units often contain multiple distinct soil types, where this is the case the values will be adjusted based on the ratio of each map unit in each crop type, and areas where data is not available for soil types that represent 60% or more of the map unit were be excluded.

I used a simple multiple linear regression model to compare expected crop yield based on soil type with a remotely sensed measure of crop productivity (average NDVI) and METRIC in order to evaluate the impact of changes in water use on crop yields while controlling for variations in productivity due to soil properties and crop type for each sub-irrigator unit. Additionally, water rights, water use and crop type data were used to determine to what extent water availability and water use determine crop selection using a multiple linear regression model.

Because water rights are administered separately in different areas with different water sources, I examined a single administrative basin, basin 35, in order to isolate the effects of water rights characteristics on water use and economic outcomes. A single basin sample is helpful in this instance because areas using different water sources the priority dates may not be directly comparable, since separate cutoff dates are used for each region. This basin had the highest number of private irrigators of any of the irrigation basins. It is located within the central portion of the aquifer, and gets surface water from the main stem of the Snake River. However, most of the irrigation rights in this basin are groundwater rights. The sample consists of approximately 1400 water rights “stacks.” Within basin 35 several important factors limit the sample size and it should be noted that this may influence the results of any model based on this sample. I calculated expected farm revenue based on soil productivity (from the SSURGO database), crop type (from the CDL) and crop prices and attempted to model farm revenue per unit area based on water rights characteristics, water use and crop productivity. Only areas with adequate soils data were included. Any area where the soil consisted of multiple components where the primary component had consisted of less than 50% of the area within each map unit was ignored. This was done so that areas with insufficient soils data to accurately predict crop production were ignored, as many of the soil areas mapped contained multiple soil components. Any areas missing adequate soils data for the specific crops being grown and fallowed lands were also ignored. This removed areas where data was missing, but it is important to note, that it may have removed areas where crops were not being grown because of unfavorable water rights or water use characteristics. The last criteria used to create this sample was the inclusion of only areas with privately held water rights. In many area water is distributed by irrigation districts or canal companies. These entities have rights to large volumes of water and have the infrastructure to deliver it to individual farmers over a spatially explicit area. Unfortunately, data describing the distribution of this water within the service areas of each canal company and irrigation district was not available. Since farmers in these areas could purchase water from a provider and I do not have access to data describing the spatial distribution of said water, one cannot know how much water each farmer in those areas feasibly has access to. Sine adequate information on the use of water rights within irrigation districts was missing the sample was limited to water rights “stacks” that contain only privately held water rights. This sample generally favors groundwater users, as surface water distribution is typically more resource intensive (requiring dams and canals) which are more likely to be held by irrigation companies.
3.4. Results

3.4.1. Comparison of Point Dropping Methods

Of the three conventional methods for dropping outliers from univariate datasets tested all performed unsatisfactorily. Dropping outliers based on a z-score of 3 standard deviations from the mean does not work well for this data set, as there is a relatively large number of extreme values in each distribution (especially in the older years), so true outliers are masked by an artificially large standard deviation, and virtually no points are being identified as outliers. This effect was more pronounced in the irrigated class (as it would naturally have a smaller deviation). For 1984 the standard deviation of the irrigated class was more than double that of 2007, (0.188 and 0.086 respectively). Using a z-score of 2 standard deviations drops an excessive number of points in the years with in the more recent years, with better training data (52 irrigated and 94 non in the 2007 data set). This was not acceptable because dropping points in recent years would shift the classification threshold values in the years where we have already shown the classification to be accurate (Chance et al., 2017). The modified z-score was also tested because it is less susceptible to effects from extreme values. A modified z-score cutoff of 3.5 performs slightly better than the standard z-score cutoff of 2 in terms of dropping less points in the years with accurate training data (39 irrigated and 73 non in the 2007 data set), but the high levels of deviation in the older data sets were too prominent, masking outliers (only dropping 190 irrigated and 22 non in the 1984 data set), and in fact dropping fewer of the non-irrigated points in 1984 than in 2007.

The one standard deviation variable cutoff method (where points that were within one standard deviation of the mean of the opposite class were dropped) was effective at dropping more points in the older data sets, and less in the new ones, but the resulting classification thresholds still varied over time (Figure 3-3). Some of this variation could be attributed to observed changes in irrigation practices and/or shifts as a result of misclassification of the control points. Observing the resulting classified maps indicated that the latter was a major source of this change, as there were large increases in misclassification of suburban areas as irrigated using this method (Figure 3-4). I tested one final method, referred to as the one standard deviation constant cutoff method, using the range of period with accurate training data to set constant point dropping cutoffs for all years. Here irrigated points with an NDMI max value below 0.163 and non-irrigated points with a value above 0.460 were dropped. This method has the clear advantage of fully removing the influence of miscategorized points in the older dataset in determining which points are dropped.
Figure 3-3. NDMI max thresholds for determining irrigated or non-irrigated lands. Results using the variable cutoff method are shown in the top row and those using the constant cutoff are shown in the bottom row. The time period with major corrections is shown on the left and the period with minor corrections is on the right.

Resulting trends in yearly classifications for the variable and constant cutoff methods are shown in Figure 3-3. While not fully eliminated, much of the upward trend in threshold values over time has been removed using the constant cutoff method. Both the $R^2$ and coefficient of a linear ordinary least squares fit are reduced by nearly half when compared to the variable cutoff method. The correlation between time and classification values is much larger during the time period predating the NAIP imagery, indicating that the trends in threshold values could be a result of errors in the classification dataset. Although this change cannot be fully eliminated, it has been greatly reduced.

In addition to reducing the threshold correlation over time, the preferred constant cutoff method also eliminates some of the large yearly variations in threshold values (and subsequent irrigation extent). 1988, for example showed an especially large change in threshold values depending on the corrections used (0.285 using the constant cutoff, 0.198 using the variable cutoff and 0.158 uncorrected). Figure 3-4 illustrates the large differences these variations in
threshold values can make on the mapped extent of agriculture, especially in urban and suburban areas where some degree of watering is common (but not as great as it is in agricultural areas).

![Figure 3-4. 1988 irrigated area surrounding Twin Falls and Kimberly, ID. (Left) irrigated extent based on the corrected threshold is shown in green, that based on the uncorrected threshold is shown in light yellow. (Right) 1988 NDMI seasonal maximum from High (white) to low (black).]

3.4.2. Regional Scale Changes

Figure 3-5 presents the long term trends (based on the preceding 5 years) in irrigated area for the SRP. For the most part the irrigated areas remain fairly constant, with some small scattered areas being added to agriculture, and some areas (mostly surrounding cities and towns) being removed. For example, the large area of red in the upper left of Figure 3-5 is the area surrounding Boise. This large area of removal is likely the result of urban and suburban expansion into formerly agricultural areas. While irrigation is still common in suburban areas, its extent is less continuous and it is of a lower intensity than irrigation for agriculture. Many of the areas removed from irrigation are suburban but there is one notable exception (visible as the largest red area in the center of Figure 3-5). This is the Bell Rapids Irrigation District. As part of water rights adjudication the water rights in this area were purchased by the state and irrigation was ceased in this area at the end of the 2004 growing season. Irrigation was inducing landslides in the adjacent Hagerman Fossil Beds National Monument. Water was being pumped from the Snake River, up to the adjacent Bruneau Plateau for irrigation, artificially rising the water table in this area, leading to instability and landslides in the area of steep slopes between the plateau and the river. These landslides damaged fossil sites, American Indian cultural sites and rare and enraged species within the national monument. Additionally, one landslide in 1987 actually destroyed a water diversion and pumping station along the Snake River (Farmer, 2003).
Figure 3-5. Long term trends in irrigation extent, 1988-2016. Green Areas were irrigated at least one year between 1984-1988, and 2011-2016.

Figure 3-6 presents the changes in reflectance values for the irrigated, non-irrigated and overall NDMI reflectance values as well as the total irrigated area for the study period. There is a slight, but statistically significant upward trend over time in the reflectance values of the irrigated class as well as in the threshold value. Overall reflectance values and non-irrigated values fluctuate year to year, but these fluctuations do not amount to any discernable trend, and thus remain relatively constant over the entire study period. Standard deviations for the irrigated class are approximately half the magnitude of those of the non-irrigated class. This is consistent with the expectation that irrigated agriculture would be more homogeneous than the rest of the landscape.
Figure 3-6. Time series plots. (Top) reflectance values of the irrigated and non-irrigated classes, as well as the classification threshold and overall average reflectance value. Blue and orange highlighted regions indicate the 95% confidence interval, based on the average values by county. (Bottom) Total irrigated area within the Snake River Plain for the study period, and reference data points for 2002 and 2007.

Total irrigated area fluctuates, between 10,450 (1984) and 12,330 km² (1993) with a mean of 11,280 km² and a standard deviation of 432 km². Fluctuations in irrigated area are relatively independent of the reflectance values in the top portion of Figure 3-6. There are large dips in the irrigated average NDMI value and in the classification threshold in 1992 and 2002, however these dips are not present in the irrigation extent for those years. In fact, both of those years have irrigation extents that are above average for our study period. This indicates that the fluctuations in the derived irrigation extent are independent of the threshold value and image reflectance used.
3.4.3. Correlation of Examined Variables

In Figure 3-7 presents $R^2$ for eight of the parameters with two goals in mind. The first aim is to see what factors are driving changes in threshold values. The second is to see if changes in the in threshold values are driving changes in the total irrigated area and the upward trend in NDMI intensity. The threshold value is correlated with the reflectance values of the image and of each class. This is to be expected, as it is calculated from what is intended to be a representative

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Figure 3-7. Matrix of scatterplots (top panel) and coefficient of correlations ($R^2$) (bottom panel) for variables examined in the time series analysis. Cells are shaded from highest $R^2$ (darkest) to lowest (lightest). Irrigated area is reported in Km² and precipitation is measured in mm.
sample of these parameters. The threshold value is not correlated with the irrigated area, which indicates that changes in the irrigated extent are not caused by our classification algorithm, but are a result of outside forces such as changes in water availability, market conditions or classification error. While the threshold value is correlated with both measures of precipitation, there is a stronger correlation between the threshold and the Jerome (single location) precipitation than with the whole watershed precipitation. This may be due to the longer data record at Jerome and/or because greenness of non-irrigated areas is more influenced by direct precipitation rather than precipitation in the adjacent mountains.

The total image value correlates strongly with the average irrigated and non-irrigated values as one would expect, since those are subsets of the total image. The total image value is well correlated with the single location precipitation (less so with the whole watershed measure). This is likely due to precipitation impacting NDMI reflectance of non-irrigated areas, which is also well correlated with precipitation, and makes up the majority of the total area but is not influenced by precipitation in the adjacent mountains. The slight correlation between the Jerome precipitation and the average irrigated reflectance, indicate that direct precipitation may have some minimal impact on reflectance within these areas. However, the lack of correlation between the average irrigated value and the whole watershed precipitation indicates that irrigation intensity is largely not determined by precipitation or surface water availability. Total irrigated area is also modestly correlated with whole watershed precipitation, so water availability is one factor impacting irrigation extent but there are likely other more important factors such as market conditions that are driving seasonal irrigation changes.

3.4.4. Changes Within Water Rights

The long term change dataset was applied to the water rights stacks to determine the potential influence of water rights on changes in irrigated area within each right. There was no obvious spatial pattern to the distribution of rights with significant additions or removal. Priority year for groundwater rights, surface water rights, and for both combined was not correlated with changes in irrigated area (the R² was less than 0.01 for each).

Rights stacks with >25% change in irrigation extent were identified to examine whether there were significant differences between those with large additions, removals, and the overall population. Rights with large decreases in irrigated area are less likely to be groundwater rights than those with additions. Only 16% rights with large removals were groundwater rights, compared to 36% with additions and 27% overall. Conversely, surface water rights are more likely to have significant areas removed from irrigation. Areas with surface water rights only (no overlapping groundwater rights) were slightly more likely to have removals than additions (7.6% of rights with large removals were for surface water only rights, compared to 4.7% of those with additions).

Among the characteristics examined, the largest difference between rights with irrigation removed and those with it added is in the size of those water rights. Rights with large irrigation extent reductions were on average 47.8 acres (with a standard deviation of 136), while those with large additions were on average 297 acres (with a standard deviation of 1196). The overall average and standard deviation were 504 and 5131 acres. The extremely large size and standard deviation of the average right is a product of the inclusion of rights held by irrigation districts and canal companies that have large service areas. None of these large areas were present in the subsets of rights with additions or removals in excess of 25%. These areas represent the area of the rights stack, the rights themselves may be much larger (especially in the case of the small
individual right that is overlain by multiple rights held by an irrigation district with a large service area).

Figure 3-8 presents a time series of the proportions of area within each water right that is irrigated each year. It should be noted that this represents the sources of water farmers have access to, and those with access to both surface and groundwater may choose to rely primarily or entirely on one source. Farms with a both groundwater and surface water rights showed the least variation year to year (standard deviations of the irrigated proportions were 5.6%, 2.3% and 4.8% for groundwater, mixed and surface water rights respectively). This is primarily because those with both surface and groundwater rights have the most secure access to water and because this represents the largest segment of rights holders. The portion of the total area irrigated in areas with only groundwater rights increased at approximately 15 square kilometers per year across the study period with an $R^2$ of 0.54. This is likely attributable, at least in part to the fact that large numbers of new groundwater rights were still being approved by IDWR into the early 90’s. The noticeable dip in groundwater irrigated area in 2001 is potentially due to Idaho Power Company’s “Irrigation Load Reduction Program” in which due to low water levels in 2001, Idaho Power was forced to purchase large amounts of high cost power from other utilities and initiated a program to pay irrigators who agreed to make large reductions to their power consumption (pumping groundwater is a power intensive process) (Howell, 2004). The relatively low groundwater irrigation levels in the mid 80’s is likely a result of the Swan Falls Agreement, which was the first major step taken in Idaho to put limits on groundwater pumping (Strong & Orr, 2016).

In 2009 the Idaho Department of Water Resources issued their first major curtailment order requiring some groundwater users to cease pumping in order to provide water to a senior

![Figure 3-8](image_url)
groundwater right held by Snake River Farms/Clear Springs Foods, which receives groundwater discharged at springs from the Snake Plain Aquifer. Most groundwater users within water districts 130 and 140 were warned the in 2008 of potential curtailments the following year, and in mid-July of 2009 groundwater users with priority dates after January 8, 1981 were ordered to stop pumping (Spackman, 2009). The order was rescinded by August of that year. I examined the total irrigated area and percentage of area irrigated within each water right in the two districts and compared rights that were curtailed, those that were warned of potential curtailment (but not actually curtailed) and those that were not covered by any potential curtailment. I found no discernable impact on the extent of irrigation either in 2009 or in the following years A time series of graphs of these results are presented in Figure 3-9. There is a noticeable decline in the percent of area irrigated in fully curtailed rights, however it occurs in 2008, prior to any notice of the curtailment, and is primarily the result of the cessation of irrigation within a single right stack (there were only 17 fully curtailed water rights stacks, so a change within one stack can have a large impact on the overall percent of area irrigated). Reductions in irrigated area likely due to the 2001 “Irrigation Load Reduction Program” are also visible in Figure 3-9 in the smaller, more groundwater dependent groups. The 2009 curtailment was issued mid-way through the growing season, be minimal impact on the total area irrigated for that year is understandable, but this does not rule out the possibility of a reduction in irrigation intensity.

Figure 3-9. Time series of percent of area irrigated by degree of impact from the Clear Springs curtailment order. 2009, the year of the curtailment order is highlighted in red. Counts of each right type are listed in parentheses. Partially curtailed rights stacks include all stacks with at least one curtailed right. For fully curtailed rights stacks, all rights within that stack were curtailed, non-impacted rights were completely unaffected but within districts 130 or 140 and those listed as outside districts were in another water district.

I test for potential responses to the 2009 curtailment order in terms of irrigation intensity using the mean NDMI pixel value within water rights stacks with differing degrees of impact.
from the curtailment order. Between 2008 and 2009 I find a small (but statistically insignificant) decrease in mean NDMI for pixels within fully curtailed water rights stacks, however I find a slight increasing in mean NDMI for partially curtailed, and rights stacks that were warned of a potential curtailment, shown in Figure 3-10A. I also observe no significant change in non-irrigated NDMI values in 2009. Changes due to seasonal variability mask the potential impact of this curtailment order, so next I examined the mean NDMI values of groups relative to that for non-impacted water rights that were within the affected irrigation districts (130 and 140) which is presented in Figure 3-10B. Again, I observe an insignificant decline in relative mean NDMI within the fully curtailed rights. I also examined mean monthly NDMI values within the 2009 growing season (Figure 3-10C). NDMI values are relatively consistent among all the groups except the fully curtailed rights stacks. Fully curtailed rights stacks showed higher NDMI values at the beginning of the growing season, a dip in July (the month before the curtailment order), lower maximum NDMI values and slightly elevated values in September. All of these variations are within one standard deviation of those for the non-impacted rights, and are thus not statistically significant. However, they could indicate heavier watering and harvest before the curtailment took place, as well as heavier watering once the curtailment was lifted in August. It should be noted that there were only 18 fully curtailed rights stacks representing approximately 4.3 square kilometers of irrigated area and makes it difficult to draw conclusions from changes within these rights.
Figure 3-10. Time series of mean NDMI (a proxy for irrigation intensity) by degree of impact from the Clear Springs curtailment order. (A) Mean NDMI of irrigated cells. (B) Mean NDMI of irrigated cells relative to the value for non-impacted rights stacks. (C) Mean monthly NDMI of irrigated cells for 2009 (the year of the curtailment order). Partially curtailed rights stacks include all stacks with at least one curtailed right, non-impacted rights were completely unaffected but within districts 130 or 140 and those listed as outside districts were in another water district.
3.4.5. Regression Analysis

A simple linear regression model was fit to the water rights sample for basin 35, finding only a slight relationship between revenue and the variables examined. Little correlation was found between water rights characteristics and water use. Regressing average evapotranspiration against surface and groundwater minimum transformed values and count of each provided an $R^2$ of 0.03. As such these factors are not well correlated and multicollinearity is not a concern in this case. While the model has a reasonable $R^2$ value of 0.35, the majority of that correlation is a result of the seasonal average NDVI (an estimated measure of productivity). If the average NDVI variable is removed the correlation drops to an $r^2$ value of less than 0.1. P values for the water rights characteristics indicate that they were at best marginally significant in determining crop revenue, the minimum p value was 0.101 for these variables. The water use characteristics may have shown significance based on their p values, but the coefficient signs were the opposite of what would be expected. They indicated that increased water use is associated with lower crop revenue, which there is little reason to believe (Table 3-2).

Table 3-2. Basin 35 multiple linear regression model results.

<table>
<thead>
<tr>
<th>Total Revenue</th>
<th>Coefficient</th>
<th>Std. Err.</th>
<th>t</th>
<th>P&gt;t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evapotranspiration Avg.</td>
<td>-0.231</td>
<td>0.049</td>
<td>-4.7</td>
<td>0</td>
</tr>
<tr>
<td>Evapotranspiration Min.</td>
<td>-0.109</td>
<td>0.041</td>
<td>-2.68</td>
<td>0.007</td>
</tr>
<tr>
<td>Evapotranspiration Std. Dev.</td>
<td>-0.318</td>
<td>0.145</td>
<td>-2.2</td>
<td>0.028</td>
</tr>
<tr>
<td>NDVI avg.</td>
<td>290.853</td>
<td>11.114</td>
<td>26.17</td>
<td>0</td>
</tr>
<tr>
<td>Surface Water Right Seniority</td>
<td>0.059</td>
<td>0.731</td>
<td>0.08</td>
<td>0.935</td>
</tr>
<tr>
<td>Ground Water Right Seniority</td>
<td>0.175</td>
<td>0.177</td>
<td>0.99</td>
<td>0.324</td>
</tr>
<tr>
<td>Surface Water Right Count</td>
<td>-41.783</td>
<td>25.477</td>
<td>-1.64</td>
<td>0.101</td>
</tr>
<tr>
<td>Groundwater Right Count</td>
<td>3.108</td>
<td>3.152</td>
<td>0.99</td>
<td>0.324</td>
</tr>
<tr>
<td>Constant</td>
<td>285.715</td>
<td>41.454</td>
<td>-6.89</td>
<td>0</td>
</tr>
</tbody>
</table>

The weak correlation between water use and especially water rights on estimated crop revenue are surprising and there is are a few likely causes for this. Error within the data set, and omitted variables are likely major factors. Sample selection may be another. Part of the problem in this case may be the selection of the year 2011, which was a relatively wet year. It is possible that there is little correlation between water rights, water use and crop production here because water was abundant within this sample, and none of the irrigators were particularly limited by their water allocation. In that case one would expect there to be little correlation between water rights, use and irrigator outcomes.

3.5. Discussion

3.5.1. Classification Techniques

A wealth of data is available in the Landsat archives, but translating those image into land use/land cover information is often limited by the availability of adequate training data. While new cloud computing platforms such as Google Earth Engine allow us to access and process huge volumes of data with relative ease, we are still limited by our ability to interpret this data.
This study presents a novel approach to classify irrigated lands during a period predating our training dataset. This naturally introduces error, but it represents a “best guess” based and the available information. Using the one standard deviation, constant cutoff method to drop misclassified points the correlation between time and classification values is reduced. This method also reduces some of the large (and likely erroneous) yearly variations in threshold values and irrigation extent. Furthermore, this paper contributes to a growing body of remote sensing studies which find that by applying simple statistics such as the median, maximum or minimum to multi-temporal data one can reliably map a wide variety of land cover regimes (Alonso, Muñoz-Carpena, Kennedy, & Murcia, 2016; Flood, 2013; Schmidt & Karnieli, 2000; Zheng, Campbell, & de Beurs, 2012). These techniques have the potential to become more commonplace as high performance cloud computing allows easier access to multi-temporal data and as more data becomes available through the Sentinel program.

3.5.2. Changes in Irrigation Extent and Intensity

Only the threshold NDMI value and the average irrigated NDMI value were correlated with time (both increasing throughout the study period). I theorize that increasing irrigated NDMI values were the result of shifts in irrigation practices, primarily the shift away from flood irrigation towards center pivot irrigation resulting in more consistent and better watering of crops in this region. This would in turn lead to increased vegetative growth, higher plant water content, lower water stress and increased NDMI values (Gao, 1996). Other developments in crop productivity, herbicides and pesticides, as well as changes in crop selection and management practices could also contribute to an increase in plant water content and increased NDMI values. While the cause for these observed increases in NDMI values cannot be definitively determined, the fact that the irrigated area is not correlated with time, indicates that the increased average irrigated values are driving the increased threshold levels, and not vice versa. If threshold shifts were driving the increased irrigated reflectance, one would expect to see a decline in irrigated area over time (assuming the true irrigated area is relatively constant) as the upward shift in threshold would cause more actually (but marginally) irrigated areas to be misclassified as non-irrigated.

Since the extent of irrigation is regulated by the IDWR, and relatively few additional water rights have been granted during our study period it is logical to expect that changes in irrigation extent were fairly minimal, and not substantially increasing over time. Although the seasonal fluctuation in irrigation extent could be partially a result of classification, or imaging errors there are likely other outside drivers of these changes such as water availability predictions, market conditions, heat, and other factors not considered here. While the overall extent of irrigation fluctuates, it does not change in any discernable pattern over time. If examined at the scale of the individual irrigator there may be more discernable drivers of change such as changes in specific water allocations or crop selection.

Within existing water rights, the intensity of irrigation (as measured by average NDMI) is relatively uniform, but there are differences in irrigation extent based on water source (groundwater versus surface water). This likely a product of Idaho’s water management structure where most irrigators have access to groundwater, and often no meaningful limits are placed on groundwater pumping.

Previous studies have found that in the ESPA revenue and irrigation extent are impacted by long term water stress (Wenchao Xu & Li, 2015; W. Xu et al., 2014). In contrast, this study finds no substantive correlation between water rights or water use on farm revenue. Furthermore,
for water rights fully curtailed in 2009 (arguably among the most water stressed) no discernable impact of this curtailment was observed. Xu found that larger irrigated areas were associated with higher revenues and predicted that junior water rights holders will leave the market due to persistent water shortages. While I found no correlation between water right size and water right seniority, I did find that smaller rights were more likely to have reduced their irrigated area over the past 33 years, and if that trend continues it is likely that some smaller rights holder may leave the market. Based on the findings here it is likely that, Xu’s findings may be largely a product of farm size, not the water right seniority. Larger water rights may have higher revenues because they are likely associated with factors that would impact their financial wellbeing. Larger farms can take advantage of economies of scale, reducing their per unit production costs. They likely have access to more capital and better more expensive equipment. They may be more able to diversify their crops mix, thus insulating them from hardships due to pests or price drops for specific crops and they may be able to negotiate better prices for their products. Conversely, smaller rights holders likely do have these factors working against them, and may be less able to compete with larger farms (Barrett, 1996; Woodhouse, 2010). This is part of a larger trend across the seen across developed world, where agriculture is shifting away from small family farms, towards larger more industrial farms (Nagayets, 2005; Sumner, 2014).

3.5.3. Sources of Uncertainty

Likely the largest source of error in this study is the training dataset. Corrections were made to account for limitations in its accuracy, but effectiveness of these corrections cannot be precisely quantified. Chance et al. evaluated the error of this methodology for two years (2002 and 2007) finding a pixel scale overall accuracy of 98.0-98.7%, the irrigated area per county had an R² of 0.970-0.981, and root mean square error (RMSE) of 45-66 square kilometers (Chance et al., 2017). The area errors were reduced slightly by the inclusion of NLCD masking in this study (R² of 0.975-0.985, and RMSE of 45-53 square kilometers). However, it is likely that older datasets are less accurate due primarily to shifts in land use at the points in the training dataset. Differences in the Landsat sensors, image timing and cloud cover all have potential impacts on the measured reflectance values. Additionally, On the ground changes in agricultural practices such as irrigation methods (shifts towards center pivot irrigation and away from flood irrigation), predominant crop type, pest management and crop improvement could all also contribute to classification errors since these practices could result in different NDMI reflectance values over time. Without additional training data it is impossible to quantify to what extent our measured shifts over time in classification values (and the upward trend in irrigated NDMI values) are a result of real changes versus being a result of classification errors. Precipitation events during the growing season likely contribute to seasonal variability in our results, impacting the NDMI values of both irrigated and non-irrigated points. Additionally, geographically isolated precipitation events could cause some non-irrigated points to be misclassified as irrigated in those areas. Although precipitation was examined in this study, I did not directly account for differences in precipitation amounts across the study region in the calculation of each threshold. Inclusion of such precipitation data could allow for a higher degree of classification accuracy, and potentially make this methodology more widely applicable to regions that receive more precipitation during the growing season.
3.5.4. Future Research

Climate change has the potential to destabilize water supplies both in the Snake River Plain and other regions across the globe. Hopefully the results, and the datasets developed in this study will be used to assess and predict the of the impacts of climate change on land-use decision-making. More detailed econometric modeling of irrigator behavior within the SRP which accounts for omitted factors such as temperature, agricultural market forces and productivity will be possible based on the results of this study. Such modeling could then be used to predict responses to various climate change scenarios as well as provide the basis for developing new policies that more efficiently balance water conservation and agricultural production, both in Idaho and other regions that depend on irrigation. Additionally, since our analysis was performed using Google Earth Engine, it is easily scalable and transferrable to other regions of the world. This makes it possible for future research to apply our methods to other regions in order to assess policy decisions there as well as compare the impacts that differences in policy across regions have on irrigation practices in those areas.

3.6. Conclusions

With minor corrections a single training dataset was applied to the entire applicable Landsat image record. Using a single cutoff value points were dropped and artificial changes within the classification threshold due to errors in the training dataset were minimized.

On the whole I find that estimated overall extent of irrigation fluctuates year to year, but remains fairly constant for the study period (1984-2016). While reflectance values and thresholds vary year to year, largely as a result of precipitation, and image variability, annual fluctuations in irrigated area are independent of threshold and reflectance values. There has been a slight increase in the NDMI reflectance values of the irrigated class during the duration of the study period. This can likely be attributed to changes in irrigation infrastructure and agricultural practices, resulting in more consistent irrigation and greener, more productive crops. The 2009 curtailment order may have had a modest, but statically insignificant impact on irrigation intensity and no discernable impact on irrigation extent. However, I do observe reductions in groundwater irrigation intensity associated with other policy measures. In general, I find no significant impact of water rights on irrigation intensity, but do find that they are associated with changes in irrigation extent over the 33-year study period. Smaller irrigators, and surface water irrigators were found to be more likely to have large reductions in the extent of their irrigation, while conversely larger, groundwater irrigators were more likely to have expanded their irrigation over the study period.

3.7. References


USGS. (2015). *National Elevation Dataset (NED) 10m*.


Chapter 4. Conclusions

In the face of potentially increasing water scarcity due to climate change, a thorough understanding of irrigator responses to changes in water availability is vital to building effective and efficient water resources policy. We use remotely sensed data to evaluate the impact of water rights characteristics on irrigation extent and intensity within the Snake River Plain. First we develop datasets which allow us to track irrigation over time, then we compare these datasets to water rights and policy decisions to evaluate their impacts.

We compare two sensors, three compositing algorithms and three spectral indices in terms of their effectiveness in distinguishing between irrigated and non-irrigated agriculture in the SRP using a binary threshold based classification. All methods performed well at the pixel scale, primarily due to limitations in the data available to develop the validation dataset. At the regional scale, we find modest differences in classification accuracy between sensors and spectral indices, but significant differences between compositing algorithms. The top performer is the seasonal-maximum algorithm, primarily because it outperforms the other approaches in appropriately classifying riparian and developed areas. The seasonal maximum algorithm reduces county scale RMSE by an average of 60% over the single-date algorithm used by of Ozdogan et al. (Ozdogan, Woodcock, Salvucci, & Demir, 2006), and yields a consistent improvement in classification accuracy across virtually all years and spectral indices. This is an efficient, computationally inexpensive method for mapping irrigated lands which can be applied to other “summer dry” arid and semi-arid climates. This mapping is done using the Google Earth Engine API, a high performance cloud computing platform which also hosts most freely available remote sensing data. Using this platform, we are able to analyze large volumes of Landsat and MODIS data with relative ease, and our analysis is easily scaled and transferred to any region of the globe.

Of the methods tested, the seasonal maximum of Landsat 5 NDMI is the most accurate in terms of county scale RMSE and R², so we apply this method to the Landsat record in order to map irrigated land use for 1984-2016. We overcome the temporal limitations of our training dataset by using a constant cutoff based on the period when our training dataset is valid in order to drop points that we believe are miss-classified. Using this record of irrigation extent, we observe changes in irrigation extent due to crop rotation, urban/suburban expansion and policy. We also observe a slight increase in the NDMI reflectance values for the irrigated class over the past 33 years. This is likely attributable to changes in irrigation infrastructure and agricultural practices which result in more consistent irrigation and more productive crops. The 2009 curtailment order may have had a modest, statically insignificant impact on irrigation intensity and no discernable impact on irrigation extent. On the whole we find no significant impact of water rights on irrigation intensity, but do find that they are correlated changes in irrigation extent, which is in line with previous studies (Cobourn, Xu, Lowe, & Mooney, 2013; Wenchao Xu & Li, 2015; W. Xu, Lowe, & Zhang, 2014). We find that smaller irrigators, and those dependent on surface water are likely to have large reductions in the extent of their irrigation over the 33-year study period, while conversely larger, groundwater irrigators were more likely to have expanded their irrigation over that time.

It appears that in general, water rights and water availability in the ESPA do not have a major impact on the quantity of water used, rather water rights primarily dictate the extent of land irrigated. However, it should be noted that our measures of water use are limited to estimates of water taken up by crops, and don’t account for infiltration to groundwater. So it is possible that irrigators with more senior rights waste more water, but it is not actually used by the crops. The view that water rights have little effect on the intensity of irrigation is reinforced
by current rights and management practices. The quantity of water granted in each water right is so great as to generally not be a limiting factor, thus only the extent is limited. Water supplied from surface sources is delivered via ditches and canals which are physically managed by regional water masters, limiting this water supply. However, the vast majority of irrigators in the ESPA have access to both surface and groundwater, which allows them access water at their convenience, regardless of river, reservoir and snowpack levels. Groundwater wells are generally privately held, and pumping volumes are not directly measured or reported to IDWR. Rather than regulating pumping volumes IDWR has essentially stopped issuing new groundwater well permits, thus limiting the total pumping volume. While this policy may have been effective in terms of limiting groundwater shortages so far, it is certainly not the most efficient or equitable way to allocate water.

The current water management structure, based on the prior appropriation doctrine, bestows water to those with the oldest right, and provides little incentive for rights holders to conserve water. Investments in drip irrigation or other, more efficient practices make no sense when irrigators with water rights have essentially unlimited water. The current policy creates an environment of have and have nots. Those with water rights typically have as much water as they can use while those without have none. If water were distributed in a different manner that encouraged efficiency, it may be possible to both expand the extent of irrigation in the SRP and use less water. Inefficient irrigation loses water in two primary ways, evaporation and infiltration. In the East Snake Plain the water that “wasted” to infiltration water generally reaches the ESPA where it is stored. This extra groundwater infiltration and aquifer recharge has largely been an unmanaged byproduct of overwatering and unlined irrigation canals (Upper Snake River Basin Water Stewardship Assessment, 2014; Willardson, Allen, & Frederiksen, 1994). However, in the future it may be possible to increase the amount of directly managed recharge in order to provide additional water storage and limit aquifer depletion. This could allow for the expansion of irrigation or provide additional water to irrigators without groundwater rights. Irrigation efficiency measures should be focused on minimizing evaporative losses, which are not stored.

While the current policy has worked up to this point, there is certainly room for improvement. If population expansion continues to increase the demand for food and water and climate change further limits and destabilizes water supplies, we may be forced to make more drastic changes to our water management institutions. Water trading markets provide one path towards a more efficient water management structure and are likely a fairly palatable option for existing rights holders. Water trading in Idaho is limited at this point, and the water rights based on irrigation extent provide another barrier to change. However, trading water between irrigators (assuming water was priced appropriately) could provide incentives to conserve water and could allow the extent and value of agriculture to expand. Future research should be focused on the impact and feasibility of water markets and other efficiency measures in this region.
Chapter 5. References


Chang, T. H., Andrew (2014). Climate Change Brief; Greater Yellowstone Ecosystem: Landscape Climate Change Vulnerability Project.


Appendix B – Developed Code

Appendix B provides Google Earth Engine API (javascript) code used for the time series analysis. Additional code used to develop the thresholds, and test various sensors, indices and algorithms can be found here: https://github.com/ericwchance/Irrigation_Extent.

// Part 1 here exports county irrigated and non irrigated cell counts (30m x 30 m) and // irrigated and non irrigated cell sums for each county for each year // as well as calculate and display maps of long term changes in irrigation extent  
// Manually set the threshold for each year:
var t1984 =0.3140625;
var t1985 =0.290625;
var t1986 =0.336458333333333;
var t1987 =0.286979166666667;
var t1988 =0.284895833333333;
var t1989 =0.3078125;
var t1990 =0.2989583333333333;
var t1991 =0.31875;
var t1992 =0.246354166666667;
var t1993 =0.353125;
var t1994 =0.320833333333333;
var t1995 =0.383854166666667;
var t1996 =0.3859375;
var t1997 =0.383333333333333;
var t1998 =0.4109375;
var t1999 =0.350520833333333;
var t2000 =0.35;
var t2001 =0.2645833333333333;
var t2002 =0.3375;
var t2003 =0.3427083333333333;
var t2004 =0.3677083333333333;
var t2005 =0.4078125;
var t2006 =0.339583333333333;
var t2007 =0.3442708333333333;
var t2008 =0.344791666666667;
var t2009 =0.383854166666667;
var t2010 =0.357291666666667;
var t2011 =0.3703125;
var t2012 =0.3171875;
var t2013 =0.3239583333333333;
var t2014 =0.330729166666667;
var t2015 =0.3859375;
var t2016 =0.410416666666667;
var total =-1;

//add counties
var fc = ee.FeatureCollection("ft:1vduVGOs9LB6TnXDC-nuNyOxtTbSI0W2nEca83iSq");
// Add Landsat 5-8 collections
// Add Landsat 5
var collection = ee.ImageCollection('LANDSAT/LT5_SR')
  .set('SENSOR_ID', 'TM');

// Add Landsat 8
var collection8 = ee.ImageCollection('LANDSAT/LC8_SR')
  .set('SENSOR_ID', 'OLI_TIRS');

// Add Landsat 7
var collection7 = ee.ImageCollection('LANDSAT/LE7_SR')
  .set('SENSOR_ID', 'TM');

// Add NDWI/NDMI for each sensor
// Add ndwi landsat 8
var addNDWI8 = function(image) {return image.addBands(image.normalizedDifference(['B5', 'B6']));};
var collection7b = collection7.map(addNDWI7);
var collection8b = collection8b.map(addNDWI8);

// Add ndwi landsat 7
var addNDWI7 = function(image) {return image.addBands(image.normalizedDifference(['B4', 'B5']));};
var collection7c = collection7b.map(addNDWI7);

// mask clouds and other bad stuff
var maskClouds = function(image) {return image.updateMask(image.select(['cfmask']).lt(0.9));};
var collection7c = collection7c.map(maskClouds);
var collection8c = collection8b.map(maskClouds);

// remove other bands
var ndwi_base5 = collection5b.select(['nd']);
var ndwi_base7 = collection7c.select(['nd']);
var ndwi_base8 = collection8c.select(['nd']);

// pull data for each growing season
var ls1984 = ndwi_base5.filterDate('1984-04-01', '1984-10-31');
var ls1985 = ndwi_base5.filterDate('1985-04-01', '1985-10-31');
var ls1986 = ndwi_base5.filterDate('1986-04-01', '1986-10-31');
var ls1987 = ndwi_base5.filterDate('1987-04-01', '1987-10-31');
var ls1988 = ndwi_base5.filterDate('1988-04-01', '1988-10-31');
var ls1989 = ndwi_base5.filterDate('1989-04-01', '1989-10-31');
```javascript
var ls1990 = ndwi_base5.filterDate('1990-04-01', '1990-10-31');
var ls1991 = ndwi_base5.filterDate('1991-04-01', '1991-10-31');
var ls1993 = ndwi_base5.filterDate('1993-04-01', '1993-10-31');
var ls1994 = ndwi_base5.filterDate('1994-04-01', '1994-10-31');
var ls1995 = ndwi_base5.filterDate('1995-04-01', '1995-10-31');
var ls1996 = ndwi_base5.filterDate('1996-04-01', '1996-10-31');
var ls1997 = ndwi_base5.filterDate('1997-04-01', '1997-10-31');
var ls1998 = ndwi_base5.filterDate('1998-04-01', '1998-10-31');
var ls1999 = ndwi_base5.filterDate('1999-04-01', '1999-10-31');
var ls2000 = ndwi_base5.filterDate('2000-04-01', '2000-10-31');
var ls2001 = ndwi_base5.filterDate('2001-04-01', '2001-10-31');
var ls2002 = ndwi_base5.filterDate('2002-04-01', '2002-10-31');
var ls2003 = ndwi_base5.filterDate('2003-04-01', '2003-10-31');
var ls2004 = ndwi_base5.filterDate('2004-04-01', '2004-10-31');
var ls2005 = ndwi_base5.filterDate('2005-04-01', '2005-10-31');
var ls2006 = ndwi_base5.filterDate('2006-04-01', '2006-10-31');
var ls2007 = ndwi_base5.filterDate('2007-04-01', '2007-10-31');
var ls2008 = ndwi_base5.filterDate('2008-04-01', '2008-10-31');
var ls2009 = ndwi_base5.filterDate('2009-04-01', '2009-10-31');
var ls2010 = ndwi_base5.filterDate('2010-04-01', '2010-10-31');
var ls2011 = ndwi_base5.filterDate('2011-04-01', '2011-10-31');
var ls2012 = ndwi_base7.filterDate('2012-04-01', '2012-10-31');
var ls2013 = ndwi_base8.filterDate('2013-04-01', '2013-10-31');
var ls2014 = ndwi_base8.filterDate('2014-04-01', '2014-10-31');
var ls2015 = ndwi_base8.filterDate('2015-04-01', '2015-10-31');
var ls2016 = ndwi_base8.filterDate('2016-04-01', '2016-10-31');

//take max for each year
var max1984 = ls1984.max();
var max1985 = ls1985.max();
var max1986 = ls1986.max();
var max1987 = ls1987.max();
var max1988 = ls1988.max();
var max1989 = ls1989.max();
var max1990 = ls1990.max();
var max1991 = ls1991.max();
var max1992 = ls1992.max();
var max1993 = ls1993.max();
var max1994 = ls1994.max();
var max1995 = ls1995.max();
var max1996 = ls1996.max();
var max1997 = ls1997.max();
var max1998 = ls1998.max();
var max1999 = ls1999.max();
var max2000 = ls2000.max();
```
var max2001 = ls2001.max();
var max2002 = ls2002.max();
var max2003 = ls2003.max();
var max2004 = ls2004.max();
var max2005 = ls2005.max();
var max2006 = ls2006.max();
var max2007 = ls2007.max();
var max2008 = ls2008.max();
var max2009 = ls2009.max();
var max2010 = ls2010.max();
var max2011 = ls2011.max();
var max2012 = ls2012.max();
var max2013 = ls2013.max();
var max2014 = ls2014.max();
var max2015 = ls2015.max();
var max2016 = ls2016.max();

// Create Classified image 1 for irrigated 0 for non for each year
var class1984 = max1984.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1984)});
var class1985 = max1985.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1985)});
var class1986 = max1986.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1986)});
var class1987 = max1987.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1987)});
var class1988 = max1988.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1988)});
var class1989 = max1989.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1989)});
var class1990 = max1990.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1990)});
var class1991 = max1991.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1991)});
var class1992 = max1992.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1992)});
var class1993 = max1993.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1993)});
var class1994 = max1994.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1994)});
var class1995 = max1995.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1995)});
var class1996 = max1996.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1996)});
var class1997 = max1997.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1997)});
var class1998 = max1998.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1998)});
var class1999 = max1999.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t1999)});
var class2000 = max2000.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2000)});
var class2001 = max2001.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2001)});
var class2002 = max2002.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2002)});
var class2003 = max2003.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2003)});
var class2004 = max2004.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2004)});
var class2005 = max2005.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2005)});
var class2006 = max2006.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2006)});
var class2007 = max2007.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2007)});
var class2008 = max2008.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2008)});
var class2009 = max2009.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2009)});
var class2010 = max2010.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2010)});
var class2011 = max2011.expression("(b('nd') > t) ? 1" + "+" + ": 0", {t: (t2011)});
var class2012 = max2012.expression("(b('nd') > t) ? 1" + ": 0", {'t': (t2012)});
var class2013 = max2013.expression("(b('nd') > t) ? 1" + ": 0", {'t': (t2013)});
var class2014 = max2014.expression("(b('nd') > t) ? 1" + ": 0", {'t': (t2014)});
var class2015 = max2015.expression("(b('nd') > t) ? 1" + ": 0", {'t': (t2015)});
var class2016 = max2016.expression("(b('nd') > t) ? 1" + ": 0", {'t': (t2016)});
var total_area = max2016.expression("(b('nd') > t) ? 1" + ": 0", {'t': (total)});

//create classified and masked image to display
var cm1984 = ee.Image(0).where(class1984.select('constant').gte(1), 1)
var cm1985 = ee.Image(0).where(class1985.select('constant').gte(1), 1)
var cm1986 = ee.Image(0).where(class1986.select('constant').gte(1), 1)
var cm1987 = ee.Image(0).where(class1987.select('constant').gte(1), 1)
var cm1988 = ee.Image(0).where(class1988.select('constant').gte(1), 1)
var cm1989 = ee.Image(0).where(class1989.select('constant').gte(1), 1)
var cm1990 = ee.Image(0).where(class1990.select('constant').gte(1), 1)
var cm1991 = ee.Image(0).where(class1991.select('constant').gte(1), 1)
var cm1992 = ee.Image(0).where(class1992.select('constant').gte(1), 1)
var cm1993 = ee.Image(0).where(class1993.select('constant').gte(1), 1)
var cm1994 = ee.Image(0).where(class1994.select('constant').gte(1), 1)
var cm1995 = ee.Image(0).where(class1995.select('constant').gte(1), 1)
var cm1996 = ee.Image(0).where(class1996.select('constant').gte(1), 1)
var cm1997 = ee.Image(0).where(class1997.select('constant').gte(1), 1)
var cm1998 = ee.Image(0).where(class1998.select('constant').gte(1), 1)
var cm1999 = ee.Image(0).where(class1999.select('constant').gte(1), 1)
var cm2000 = ee.Image(0).where(class2000.select('constant').gte(1), 1)
var cm2001 = ee.Image(0).where(class2001.select('constant').gte(1), 1)
var cm2002 = ee.Image(0).where(class2002.select('constant').gte(1), 1)
var cm2003 = ee.Image(0).where(class2003.select('constant').gte(1), 1)
var cm2004 = ee.Image(0).where(class2004.select('constant').gte(1), 1)
var cm2005 = ee.Image(0).where(class2005.select('constant').gte(1), 1)
var cm2006 = ee.Image(0).where(class2006.select('constant').gte(1), 1)
var cm2007 = ee.Image(0).where(class2007.select('constant').gte(1), 1)
var cm2008 = ee.Image(0).where(class2008.select('constant').gte(1), 1)
var cm2009 = ee.Image(0).where(class2009.select('constant').gte(1), 1)
var cm2010 = ee.Image(0).where(class2010.select('constant').gte(1), 1)
var cm2011 = ee.Image(0).where(class2011.select('constant').gte(1), 1)
var cm2012 = ee.Image(0).where(class2012.select('constant').gte(1), 1)
var cm2013 = ee.Image(0).where(class2013.select('constant').gte(1), 1)
var cm2014 = ee.Image(0).where(class2014.select('constant').gte(1), 1)
var cm2015 = ee.Image(0).where(class2015.select('constant').gte(1), 1)
var cm2016 = ee.Image(0).where(class2016.select('constant').gte(1), 1)

/////////Display
///////////unblock off line to display image for that year///////////
//Map.addLayer(cm1984.mask(cm1984), {palette:'369b47'}, 'classified_1984');
// Map.addLayer(max1984, {palette: '000000, FFFFFF', min: -2, max: .6}, 'ndmi max 1984');
// Map.addLayer(cm1985.mask(cm1985), {palette: '369b47'}, 'classified_1985');
// Map.addLayer(cm1986.mask(cm1986), {palette: '369b47'}, 'classified_1986');
// Map.addLayer(cm1987.mask(cm1987), {palette: '369b47'}, 'classified_1987');
// Map.addLayer(cm1989.mask(cm1989), {palette: '369b47'}, 'classified_1989');
// Map.addLayer(cm1990.mask(cm1990), {palette: '369b47'}, 'classified_1990');
// Map.addLayer(cm1993.mask(cm1993), {palette: '369b47'}, 'classified_1993');
// Map.addLayer(cm1994.mask(cm1994), {palette: '369b47'}, 'classified_1994');
// Map.addLayer(cm1995.mask(cm1995), {palette: '369b47'}, 'classified_1995');
// Map.addLayer(cm1996.mask(cm1996), {palette: '369b47'}, 'classified_1996');
// Map.addLayer(cm1997.mask(cm1997), {palette: '369b47'}, 'classified_1997');
// Map.addLayer(cm1998.mask(cm1998), {palette: '369b47'}, 'classified_1998');
// Map.addLayer(cm1999.mask(cm1999), {palette: '369b47'}, 'classified_1999');
// Map.addLayer(cm2000.mask(cm2000), {palette: '369b47'}, 'classified_2000');
// Map.addLayer(cm2001.mask(cm2001), {palette: '369b47'}, 'classified_2001');
// Map.addLayer(cm2002.mask(cm2002), {palette: '369b47'}, 'classified_2002');
// Map.addLayer(cm2003.mask(cm2003), {palette: '369b47'}, 'classified_2003');
// Map.addLayer(cm2004.mask(cm2004), {palette: '369b47'}, 'classified_2004');
// Map.addLayer(cm2005.mask(cm2005), {palette: '369b47'}, 'classified_2005');
// Map.addLayer(cm2006.mask(cm2006), {palette: '369b47'}, 'classified_2006');
// Map.addLayer(cm2007.mask(cm2007), {palette: '369b47'}, 'classified_2007');
// Map.addLayer(cm2008.mask(cm2008), {palette: '369b47'}, 'classified_2008');
// Map.addLayer(cm2009.mask(cm2009), {palette: '369b47'}, 'classified_2009');
// Map.addLayer(cm2010.mask(cm2010), {palette: '369b47'}, 'classified_2010');
// Map.addLayer(cm2011.mask(cm2011), {palette: '369b47'}, 'classified_2011');
// Map.addLayer(cm2012.mask(cm2012), {palette: '369b47'}, 'classified_2012');
// Map.addLayer(cm2013.mask(cm2013), {palette: '369b47'}, 'classified_2013');
// Map.addLayer(cm2014.mask(cm2014), {palette: '369b47'}, 'classified_2014');
// Map.addLayer(cm2015.mask(cm2015), {palette: '369b47'}, 'classified_2015');
// Map.addLayer(cm2016.mask(cm2016), {palette: '00ff47'}, 'classified_2016');

/////////// make 5 year history layers (1 if irrigated any time in the past 5 years)
// create the classpile image, one image with the bands for the classification for each year
// Make the 5 year history for each year
Map.addLayer(classpile);
var lt_class1988 =
classpile.expression("((b('constant_31')+b('constant_2')+b('constant_1_1')+b('constant_1')+b('constant')) > .9) ? 1" + ": 0");
var lt_class1989 =
classpile.expression("((b('constant_3')+b('constant_2')+b('constant_1_1')+b('constant_1')+b('constant')) > .9) ? 1" + ": 0");
var lt_class1990 =
classpile.expression("((b('constant_4')+b('constant_3')+b('constant_2')+b('constant_1_1')+b('constant_1')) > .9) ? 1" + ": 0");
var lt_class1991 =
classpile.expression("((b('constant_5')+b('constant_4')+b('constant_3')+b('constant_2')+b('constant_1_1')) > .9) ? 1" + ": 0");
var lt_class1992 =
classpile.expression("((b('constant_6')+b('constant_5')+b('constant_4')+b('constant_3')+b('constant_2')) > .9) ? 1" + ": 0");
var lt_class1993 =
classpile.expression("((b('constant_7')+b('constant_6')+b('constant_5')+b('constant_4')+b('constant_3')) > .9) ? 1" + ": 0");
var lt_class1994 =
classpile.expression("((b('constant_8')+b('constant_7')+b('constant_6')+b('constant_5')+b('constant_4')) > .9) ? 1" + ": 0");
var lt_class1995 =
classpile.expression("((b('constant_9')+b('constant_8')+b('constant_7')+b('constant_6')+b('constant_5')) > .9) ? 1" + ": 0");
var lt_class1996 =
classpile.expression("((b('constant_10')+b('constant_9')+b('constant_8')+b('constant_7')+b('constant_6')) > .9) ? 1" + ": 0");
var lt_class1997 =
classpile.expression("((b('constant_11')+b('constant_10')+b('constant_9')+b('constant_8')+b('constant_7')) > .9) ? 1" + ": 0");
var lt_class1998 =
classpile.expression("((b('constant_12')+b('constant_11')+b('constant_10')+b('constant_9')+b('constant_8')) > .9) ? 1" + ": 0");
var lt_class1999 =
classpile.expression("((b('constant_13')+b('constant_12')+b('constant_11')+b('constant_10')+b('constant_9')) > .9) ? 1" + ": 0");
var lt_class2000 =
classpile.expression("((b('constant_14')+b('constant_13')+b('constant_12')+b('constant_11')+b('constant_10')) > .9) ? 1" + ": 0");
var lt_class2001 =
classpile.expression("((b('constant_15')+b('constant_14')+b('constant_13')+b('constant_12')+b('constant_11')) > .9) ? 1" + ": 0");
var lt_class2002 =
classpile.expression("((b('constant_16')+b('constant_15')+b('constant_14')+b('constant_13')+b('constant_12')) > .9) ? 1" + ": 0");
var lt_class2003 =
classpile.expression("((b('constant_17')+b('constant_16')+b('constant_15')+b('constant_14')+b('constant_13')) > .9) ? 1" + ": 0");
var lt_class2004 =
classpile.expression("((b('constant_18')+b('constant_17')+b('constant_16')+b('constant_15')+b('constant_14')) > .9) ? 1" + ": 0");
var lt_class2005 =
classpile.expression("((b('constant_19')+b('constant_18')+b('constant_17')+b('constant_16')+b('constant_15')) > .9) ? 1" + ": 0");
var lt_class2006 =
classpile.expression("((b('constant_20')+b('constant_19')+b('constant_18')+b('constant_17')+b('constant_16')) > .9) ? 1" + ": 0");
var lt_class2007 =
classpile.expression("((b('constant_21')+b('constant_20')+b('constant_19')+b('constant_18')+b('constant_17')) > .9) ? 1" + ": 0");
var lt_class2008 =
classpile.expression("((b('constant_22')+b('constant_21')+b('constant_20')+b('constant_19')+b('constant_18')) > .9) ? 1" + ": 0");
var lt_class2009 =
classpile.expression("((b('constant_23')+b('constant_22')+b('constant_21')+b('constant_20')+b('constant_19')) > .9) ? 1" + ": 0");
var lt_class2010 =
classpile.expression("((b('constant_24')+b('constant_23')+b('constant_22')+b('constant_21')+b('constant_20')) > .9) ? 1" + ": 0");
var lt_class2011 =
classpile.expression("((b('constant_25')+b('constant_24')+b('constant_23')+b('constant_22')+b('constant_21')) > .9) ? 1" + ": 0");
var lt_class2012 =
classpile.expression("((b('constant_26')+b('constant_25')+b('constant_24')+b('constant_23')+b('constant_22')) > .9) ? 1" + ": 0");
var lt_class2013 =
classpile.expression("((b('constant_27')+b('constant_26')+b('constant_25')+b('constant_24')+b('constant_23')) > .9) ? 1" + ": 0");
var lt_class2014 =
classpile.expression("((b('constant_28')+b('constant_27')+b('constant_26')+b('constant_25')+b('constant_24')) > .9) ? 1" + ": 0");
var lt_class2015 =
classpile.expression("((b('constant_29')+b('constant_28')+b('constant_27')+b('constant_26')+b('constant_25')) > .9) ? 1" + ": 0");
//var lt_class2016 =
classpile.expression("((b('constant_30')+b('constant_29')+b('constant_28')+b('constant_27')+b('constant_26')) > .9) ? 1" + ": 0");
//2016 excluding using 2011 instead of 2012 (cause landsat 7 sucks)
var lt_class2016 =
classpile.expression("((b('constant_30')+b('constant_29')+b('constant_28')+b('constant_27')+b('constant_26')) > .9) ? 1" + ": 0");
/// long term differences
/// Manually Change years in here!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
var classified_old = lt_class1988.expression("(b('constant') > .9) ? 10" + ": 0");
var classified_new = lt_class2016.expression("(b('constant') > .9) ? 5" + ": 0");

// Add old and new together to make a change map
var combo = classified_old.add(classified_new);

// Define an SLD style of discrete intervals to apply to the image (to color each class differently).
var sld_intervals =
'"<RasterSymbolizer>" +
'"<ColorMap type="intervals" extended="false" >" +
'"<ColorMapEntry color="#000000" quantity="0" label="non"/>" +
'"<ColorMapEntry color="#0101FF" quantity="5" label="added"/>" +
'"<ColorMapEntry color="#FF0101" quantity="10" label="removed"/>" +
'"<ColorMapEntry color="#369b47" quantity="15" label="continuous"/>" +
'"</ColorMap>" +
'"</RasterSymbolizer>"';
// Map.addLayer(combo.sldStyle(sld_intervals), {}, 'Changes');

///////////DISPLAY CHANGES
// changes without NLCD masking: (blocked)
// Map.addLayer(combo.sldStyle(sld_intervals).mask(combo.sldStyle(sld_intervals)), {}, 'classified_and_masked_Changes');
// NLCD 2006 masking
var a2006= ee.Image('USGS/NLCD/NLCD2006');
// remove other bands
var l06 = a2006.select(['landcover']);
// mask everything (including urban)
// var all_mask = l06.expression("(b('landcover') > 49) ? 1" + ": 0");
// var combo2 = combo.multiply(all_mask)
// Map.addLayer(all_mask);
// Map.addLayer(combo2.sldStyle(sld_intervals).mask(combo2.sldStyle(sld_intervals)), {}, 'classified_and_masked2_Changes');

// mask everything but urban
var a = l06.expression("(b('landcover') > 20) ? 1" + ": 0");
var b = l06.expression("(b('landcover') < 30 ) ? 1" + ": 0");
// var c = l06.expression("(b('landcover') > 40 ) ? 1" + ": 0");
var c = l06.expression("(b('landcover') > 53 ) ? 1" + ": 0");
var xx = a.multiply(b);
var xxx = xx.add(c);
var combo3 = combo.multiply(xxx);
Map.addLayer(combo3.sldStyle(sld_intervals).mask(combo3.sldStyle(sld_intervals)),{},'classified_and_masked3_Changes');

//mask water and barren areas only
var a = l06.expression("\((b('landcover') > 20) ? 1" + ": 0\)");
var z = l06.expression("\((b('landcover') == 31) ? 0" + ": 1\)");
var xxxx = a.multiply(z);
var total_area_msked = total_area.multiply(xxxx);
//display to make sure its working right
//Map.addLayer(total_area_msked, {palette: '000000, FFFFFF', min: 0, max: 1},'classified_xtra_mask');
//Map.addLayer(cm2016.mask(cm2016),{palette:'00ff47'},'classified_2016');
Map.addLayer(fc, {color: 'FFFFFF'}, 'From Fusion Table');


//Masking and exporting extent for each year & county

////////////////////////Masking and exporting extent for each year & county

////////////////////////Irrigated count

//masking for each year
var m_class1984 = class1984.multiply(xxxx);
var m_class1985 = class1985.multiply(xxxx);
var m_class1986 = class1986.multiply(xxxx);
var m_class1987 = class1987.multiply(xxxx);
var m_class1988 = class1988.multiply(xxxx);
var m_class1989 = class1989.multiply(xxxx);
var m_class1990 = class1990.multiply(xxxx);
var m_class1991 = class1991.multiply(xxxx);
var m_class1992 = class1992.multiply(xxxx);
var m_class1993 = class1993.multiply(xxxx);
var m_class1994 = class1994.multiply(xxxx);
var m_class1995 = class1995.multiply(xxxx);
var m_class1996 = class1996.multiply(xxxx);
var m_class1997 = class1997.multiply(xxxx);
var m_class1998 = class1998.multiply(xxxx);
var m_class1999 = class1999.multiply(xxxx);
var m_class2000 = class2000.multiply(xxxx);
var m_class2001 = class2001.multiply(xxxx);
var m_class2002 = class2002.multiply(xxxx);
var m_class2003 = class2003.multiply(xxxx);
var m_class2004 = class2004.multiply(xxxx);
var m_class2005 = class2005.multiply(xxxx);
var m_class2006 = class2006.multiply(xxxx);
var m_class2007 = class2007.multiply(xxxx);
var m_class2008 = class2008.multiply(xxxx);
var m_class2009 = class2009.multiply(xxxx);
var m_class2010 = class2010.multiply(xxxx);
var m_class2011 = class2011.multiply(xxxx);
var m_class2012 = class2012.multiply(xxxx);
var m_class2013 = class2013.multiply(xxxx);
var m_class2014 = class2014.multiply(xxxx);
var m_class2015 = class2015.multiply(xxxx);
var m_class2016 = class2016.multiply(xxxx);

//create table for each year
var count1984 = m_class1984.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count1985 = m_class1985.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count1986 = m_class1986.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count1990 = m_class1990.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count1996 = m_class1996.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count1999 = m_class1999.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2002 = m_class2002.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2005 = m_class2005.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2006 = m_class2006.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2009 = m_class2009.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2010 = m_class2010.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2011 = m_class2011.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2012 = m_class2012.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2013 = m_class2013.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2014 = m_class2014.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2015 = m_class2015.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var count2016 = m_class2016.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});

//export table for each year and county
Export.table.toDrive(count1984, "irr_count_1984");
Export.table.toDrive(count1985, "irr_count_1985");
Export.table.toDrive(count1986, "irr_count_1986");
Export.table.toDrive(count1987, "irr_count_1987");
Export.table.toDrive(count1988, "irr_count_1988");
Export.table.toDrive(count1989, "irr_count_1989");
Export.table.toDrive(count1990, "irr_count_1990");
Export.table.toDrive(count1991, "irr_count_1991");
Export.table.toDrive(count1992, "irr_count_1992");
Export.table.toDrive(count1993, "irr_count_1993");
Export.table.toDrive(count1994, "irr_count_1994");
Export.table.toDrive(count1995, "irr_count_1995");
Irrigated sums

masking for each year

defines sums for each year:

```
defines sums for each year:
```
var sumz2005 = m_class2005.multiply(max2005);
var sumz2006 = m_class2006.multiply(max2006);
var sumz2007 = m_class2007.multiply(max2007);
var sumz2008 = m_class2008.multiply(max2008);
var sumz2009 = m_class2009.multiply(max2009);
var sumz2010 = m_class2010.multiply(max2010);
var sumz2011 = m_class2011.multiply(max2011);
var sumz2012 = m_class2012.multiply(max2012);
var sumz2013 = m_class2013.multiply(max2013);
var sumz2014 = m_class2014.multiply(max2014);
var sumz2015 = m_class2015.multiply(max2015);
var sumz2016 = m_class2016.multiply(max2016);

//create tables

//export irrigated sums for each county
Export.table.toDrive(sum1984, "irr_sum_1984");
Export.table.toDrive(sum1985, "irr_sum_1985");
Export.table.toDrive(sum1986, "irr_sum_1986");
Export.table.toDrive(sum1987, "irr_sum_1987");
Export.table.toDrive(sum1988, "irr_sum_1988");
Export.table.toDrive(sum1989, "irr_sum_1989");
Export.table.toDrive(sum1990, "irr_sum_1990");
Export.table.toDrive(sum1991, "irr_sum_1991");
Export.table.toDrive(sum1992, "irr_sum_1992");
Export.table.toDrive(sum1993, "irr_sum_1993");
Export.table.toDrive(sum1994, "irr_sum_1994");
Export.table.toDrive(sum1995, "irr_sum_1995");
Export.table.toDrive(sum1996, "irr_sum_1996");
Export.table.toDrive(sum1997, "irr_sum_1997");
Export.table.toDrive(sum1998, "irr_sum_1998");
Export.table.toDrive(sum1999, "irr_sum_1999");
Export.table.toDrive(sum2000, "irr_sum_2000");
Export.table.toDrive(sum2001, "irr_sum_2001");
Export.table.toDrive(sum2002, "irr_sum_2002");
Export.table.toDrive(sum2003, "irr_sum_2003");
Export.table.toDrive(sum2004, "irr_sum_2004");
Export.table.toDrive(sum2005, "irr_sum_2005");
Export.table.toDrive(sum2006, "irr_sum_2006");
Export.table.toDrive(sum2007, "irr_sum_2007");
Export.table.toDrive(sum2008, "irr_sum_2008");
Export.table.toDrive(sum2009, "irr_sum_2009");
Export.table.toDrive(sum2010, "irr_sum_2010");
Export.table.toDrive(sum2011, "irr_sum_2011");
Export.table.toDrive(sum2012, "irr_sum_2012");
Export.table.toDrive(sum2013, "irr_sum_2013");
Export.table.toDrive(sum2014, "irr_sum_2014");
Export.table.toDrive(sum2015, "irr_sum_2015");
Export.table.toDrive(sum2016, "irr_sum_2016");

// Create non_classified image invert: 1 for non 0 for irrigated for each year
var non_class1984 = max1984.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1984)});
var non_class1985 = max1985.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1985)});
var non_class1986 = max1986.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1986)});
var non_class1987 = max1987.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1987)});
var non_class1988 = max1988.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1988)});
var non_class1989 = max1989.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1989)});
var non_class1990 = max1990.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1990)});
var non_class1991 = max1991.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1991)});
var non_class1992 = max1992.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1992)});
var non_class1993 = max1993.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1993)});
var non_class1994 = max1994.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1994)});
var non_class1995 = max1995.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1995)});
var non_class1996 = max1996.expression("(b'(nd') < t) ? 1" + ": 0", {t': (t1996)});
var non_class1997 = max1997.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t1997)});
var non_class1998 = max1998.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t1998)});
var non_class1999 = max1999.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t1999)});
var non_class2000 = max2000.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2000)});
var non_class2001 = max2001.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2001)});
var non_class2002 = max2002.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2002)});
var non_class2003 = max2003.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2003)});
var non_class2004 = max2004.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2004)});
var non_class2005 = max2005.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2005)});
var non_class2006 = max2006.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2006)});
var non_class2007 = max2007.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2007)});
var non_class2008 = max2008.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2008)});
var non_class2009 = max2009.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2009)});
var non_class2010 = max2010.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2010)});
var non_class2011 = max2011.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2011)});
var non_class2012 = max2012.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2012)});
var non_class2013 = max2013.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2013)});
var non_class2014 = max2014.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2014)});
var non_class2015 = max2015.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2015)});
var non_class2016 = max2016.expression("(b('nd') < t) ? 1" + ": 0", {'t': (t2016)});

create count of non-irrigated cells by county
//masking for each year
var mnon_class1984 = non_class1984.multiply(xxxx);
var mnon_class1985 = non_class1985.multiply(xxxx);
var mnon_class1986 = non_class1986.multiply(xxxx);
var mnon_class1987 = non_class1987.multiply(xxxx);
var mnon_class1988 = non_class1988.multiply(xxxx);
var mnon_class1989 = non_class1989.multiply(xxxx);
var mnon_class1990 = non_class1990.multiply(xxxx);
var mnon_class1991 = non_class1991.multiply(xxxx);
var mnon_class1992 = non_class1992.multiply(xxxx);
var mnon_class1993 = non_class1993.multiply(xxxx);
var mnon_class1994 = non_class1994.multiply(xxxx);
var mnon_class1995 = non_class1995.multiply(xxxx);
var mnon_class1996 = non_class1996.multiply(xxxx);
var mnon_class1997 = non_class1997.multiply(xxxx);
var mnon_class1998 = non_class1998.multiply(xxxx);
var mnon_class1999 = non_class1999.multiply(xxxx);
var mnon_class2000 = non_class2000.multiply(xxxx);
var mnon_class2001 = non_class2001.multiply(xxxx);
var mnon_class2002 = non_class2002.multiply(xxxx);
var mnon_class2003 = non_class2003.multiply(xxxx);
var mnon_class2004 = non_class2004.multiply(xxxx);
var mnon_class2005 = non_class2005.multiply(xxxx);
var mnon_class2006 = non_class2006.multiply(xxxx);
var mnon_class2007 = non_class2007.multiply(xxxx);
var mnon_class2008 = non_class2008.multiply(xxxx);
var mnon_class2009 = non_class2009.multiply(xxxx);
var mnon_class2010 = non_class2010.multiply(xxxx);
var mnon_class2011 = non_class2011.multiply(xxxx);
var mnon_class2012 = non_class2012.multiply(xxxx);
var mnon_class2013 = non_class2013.multiply(xxxx);
var mnon_class2014 = non_class2014.multiply(xxxx);
var mnon_class2015 = non_class2015.multiply(xxxx);
var mnon_class2016 = non_class2016.multiply(xxxx);

// apply to county/year and make a table
var non_count1986 = mnon_class1986.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_count1990 = mnon_class1990.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_count2006 = mnon_class2006.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_count2010 = mnon_class2010.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_count2012 = mnon_class2012.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_count2013 = mnon_class2013.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_count2014 = mnon_class2014.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_count2015 = mnon_class2015.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_count2016 = mnon_class2016.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});

//export non-irrigated cell count by county for each year
Export.table.toDrive (non_count1984, "non_count_1984");
Export.table.toDrive (non_count1985, "non_count_1985");
Export.table.toDrive (non_count1986, "non_count_1986");
Export.table.toDrive (non_count1987, "non_count_1987");
Export.table.toDrive (non_count1988, "non_count_1988");
Export.table.toDrive (non_count1989, "non_count_1989");
Export.table.toDrive (non_count1990, "non_count_1990");
Export.table.toDrive (non_count1991, "non_count_1991");
Export.table.toDrive (non_count1992, "non_count_1992");
Export.table.toDrive (non_count1993, "non_count_1993");
Export.table.toDrive (non_count1994, "non_count_1994");
Export.table.toDrive (non_count1995, "non_count_1995");
Export.table.toDrive (non_count1996, "non_count_1996");
Export.table.toDrive (non_count1997, "non_count_1997");
Export.table.toDrive (non_count1998, "non_count_1998");
Export.table.toDrive (non_count1999, "non_count_1999");
Export.table.toDrive (non_count2000, "non_count_2000");
Export.table.toDrive (non_count2001, "non_count_2001");
Export.table.toDrive (non_count2002, "non_count_2002");
Export.table.toDrive (non_count2003, "non_count_2003");
Export.table.toDrive (non_count2004, "non_count_2004");
Export.table.toDrive (non_count2005, "non_count_2005");
Export.table.toDrive (non_count2006, "non_count_2006");
Export.table.toDrive (non_count2007, "non_count_2007");
Export.table.toDrive (non_count2008, "non_count_2008");
Export.table.toDrive (non_count2009, "non_count_2009");
Export.table.toDrive (non_count2010, "non_count_2010");
Export.table.toDrive (non_count2011, "non_count_2011");
Export.table.toDrive (non_count2012, "non_count_2012");
Export.table.toDrive (non_count2013, "non_count_2013");
Export.table.toDrive (non_count2014, "non_count_2014");
Export.table.toDrive (non_count2015, "non_count_2015");
Export.table.toDrive (non_count2016, "non_count_2016");

// create non-irrigated cell sums for each year
var non_sumz1984 = mnon_class1984.multiply(max1984);
var non_sumz1985 = mnon_class1985.multiply(max1985);
var non_sumz1986 = mnon_class1986.multiply(max1986);
var non_sumz1987 = mnon_class1987.multiply(max1987);
var non_sumz1988 = mnon_class1988.multiply(max1988);
var non_sumz1989 = mnon_class1989.multiply(max1989);
var non_sumz1990 = mnon_class1990.multiply(max1990);
var non_sumz1991 = mnon_class1991.multiply(max1991);
var non_sumz1992 = mnon_class1992.multiply(max1992);
var non_sumz1993 = mnon_class1993.multiply(max1993);
var non_sumz1994 = mnon_class1994.multiply(max1994);
var non_sumz1995 = mnon_class1995.multiply(max1995);
var non_sumz1996 = mnon_class1996.multiply(max1996);
var non_sumz1997 = mnon_class1997.multiply(max1997);
var non_sumz1998 = mnon_class1998.multiply(max1998);
var non_sumz1999 = mnon_class1999.multiply(max1999);
var non_sumz2000 = mnon_class2000.multiply(max2000);
var non_sumz2001 = mnon_class2001.multiply(max2001);
var non_sumz2002 = mnon_class2002.multiply(max2002);
var non_sum2003 = mnon_class2003.multiply(max2003);
var non_sum2004 = mnon_class2004.multiply(max2004);
var non_sum2005 = mnon_class2005.multiply(max2005);
var non_sum2006 = mnon_class2006.multiply(max2006);
var non_sum2007 = mnon_class2007.multiply(max2007);
var non_sum2008 = mnon_class2008.multiply(max2008);
var non_sum2009 = mnon_class2009.multiply(max2009);
var non_sum2010 = mnon_class2010.multiply(max2010);
var non_sum2011 = mnon_class2011.multiply(max2011);
var non_sum2012 = mnon_class2012.multiply(max2012);
var non_sum2013 = mnon_class2013.multiply(max2013);
var non_sum2014 = mnon_class2014.multiply(max2014);
var non_sum2015 = mnon_class2015.multiply(max2015);
var non_sum2016 = mnon_class2016.multiply(max2016);

//make table of non-irrigated cell sum for each year & county
var non_sum1984 = non_sumz1984.reduceRegions({collection: fc, reducer: ee.Reducer.sum(),
  scale: 30, crs: "EPSG:4326"});
var non_sum1985 = non_sumz1985.reduceRegions({collection: fc, reducer: ee.Reducer.sum(),
  scale: 30, crs: "EPSG:4326"});
var non_sum1986 = non_sumz1986.reduceRegions({collection: fc, reducer: ee.Reducer.sum(),
  scale: 30, crs: "EPSG:4326"});
  scale: 30, crs: "EPSG:4326"});
  scale: 30, crs: "EPSG:4326"});
  scale: 30, crs: "EPSG:4326"});
var non_sum1990 = non_sumz1990.reduceRegions({collection: fc, reducer: ee.Reducer.sum(),
  scale: 30, crs: "EPSG:4326"});
  scale: 30, crs: "EPSG:4326"});
  scale: 30, crs: "EPSG:4326"});
  scale: 30, crs: "EPSG:4326"});
  scale: 30, crs: "EPSG:4326"});
  scale: 30, crs: "EPSG:4326"});
var non_sum1996 = non_sumz1996.reduceRegions({collection: fc, reducer: ee.Reducer.sum(),
  scale: 30, crs: "EPSG:4326"});
  scale: 30, crs: "EPSG:4326"});
var non_sum2006 = non_sumz2006.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_sum2010 = non_sumz2010.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_sum2012 = non_sumz2012.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_sum2013 = non_sumz2013.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
var non_sum2016 = non_sumz2016.reduceRegions({collection: fc, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});

// export table of sum of non irrigated NDMI values by county for each year
Export.table.toDrive(non_sum1984, "non_sum_1984");
Export.table.toDrive(non_sum1985, "non_sum_1985");
Export.table.toDrive(non_sum1986, "non_sum_1986");
Export.table.toDrive(non_sum1987, "non_sum_1987");
Export.table.toDrive(non_sum1988, "non_sum_1988");
Export.table.toDrive(non_sum1989, "non_sum_1989");
Export.table.toDrive(non_sum1990, "non_sum_1990");
Export.table.toDrive(non_sum1991, "non_sum_1991");
Export.table.toDrive(non_sum1992, "non_sum_1992");
Export.table.toDrive(non_sum1993, "non_sum_1993");
Export.table.toDrive(non_sum1994, "non_sum_1994");
Export.table.toDrive(non_sum1995, "non_sum_1995");
Export.table.toDrive(non_sum1996, "non_sum_1996");
Export.table.toDrive(non_sum1997, "non_sum_1997");
Export.table.toDrive(non_sum1998, "non_sum_1998");
Export.table.toDrive(non_sum1999, "non_sum_1999");
Export.table.toDrive(non_sum2000, "non_sum_2000");
Export.table.toDrive(non_sum2001, "non_sum_2001");
Export.table.toDrive(non_sum2002, "non_sum_2002");
Export.table.toDrive(non_sum2003, "non_sum_2003");
Export.table.toDrive(non_sum2004, "non_sum_2004");
Export.table.toDrive(non_sum2005, "non_sum_2005");
Export.table.toDrive(non_sum2006, "non_sum_2006");
Export.table.toDrive(non_sum2007, "non_sum_2007");
Export.table.toDrive(non_sum2008, "non_sum_2008");
Export.table.toDrive(non_sum2009, "non_sum_2009");
Export.table.toDrive(non_sum2010, "non_sum_2010");
Export.table.toDrive(non_sum2011, "non_sum_2011");
Export.table.toDrive(non_sum2012, "non_sum_2012");
Export.table.toDrive(non_sum2013, "non_sum_2013");
Export.table.toDrive(non_sum2014, "non_sum_2014");
Export.table.toDrive(non_sum2015, "non_sum_2015");
Export.table.toDrive(non_sum2016, "non_sum_2016");

//Part 2 exports annual changes in irrigation extent by water right (cell counts)
//export one table that sums the long term changes within each right and
//export one table for each year with the extent of irrigation in each right (which can be
//combined manually, and analyzed outside of GEE.

Выборка значений по водным правам

var wr = ee.FeatureCollection("ft:1nbylJCuSfgcOGe5k5LKaeKPDG7-4VcPb9wydqKaR");
Map.addLayer(wr, {color: 'FF00FF'}, 'Water_Rights');

//long term differences
var classified_old_b = lt_class1988.expression('(b('constant') > .9) ? 1 : 0');
var classified_new_b = lt_class2016.expression('(b('constant') > .9) ? 1 : 0');

subtract the two classified images to get the difference
var combo_b = classified_new.subtract(classified_old);

// Define an SLD style of discrete intervals to apply to the difference image.
var sld_intervals_b =
'<RasterSymbolizer>' +
' <ColorMap type="intervals" extended="false"/>
  <ColorMapEntry color="#000000" quantity="0" label="non or continous"/>
  <ColorMapEntry color="#0101FF" quantity="1" label="added"/>
  <ColorMapEntry color="#FF0101" quantity="-1" label="removed"/>
</ColorMap>
</RasterSymbolizer>;' +
//display difference image (unmasked)
Map.addLayer(combo_b.sldStyle(sld_intervals_b), {}, difference);
//display the masked (everything but urban) version on the change map
var combo3_b = combo_b.multiply(xxx);
Map.addLayer(combo3_b.sldStyle(sld_intervals_b).mask(combo3_b.sldStyle(sld_intervals)), {}, masked_differnce);

/////////// Exporting long term changes in extent for each water right
var lt_changez = combo3_b.reduceRegions({collection: wr, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326"});
//Export.table.toDrive(lt_changez, "lt_changes_1984to2016_by_right_pile");

/////////// Exporting irrigation extent by water right tables for each year
// create tables (sums are the count of irrigated cells in each right), this and the next part can be
//repeated with all the thresholds set to -1 to get the total cell count for each water right for each
//year (as cell counts can vary slightly based on pixel alignment) .
var rights2013 = cm2013.reduceRegions({collection: wr, reducer: ee.Reducer.sum(), scale: 30, crs: "EPSG:4326");

//export tables
Export.table.toDrive(rights1984, "rights1984");
Export.table.toDrive(rights1985, "rights1985");
Export.table.toDrive(rights1986, "rights1986");
Export.table.toDrive(rights1987, "rights1987");
Export.table.toDrive(rights1988, "rights1988");
Export.table.toDrive(rights1989, "rights1989");
Export.table.toDrive(rights1990, "rights1990");
Export.table.toDrive(rights1991, "rights1991");
Export.table.toDrive(rights1992, "rights1992");
Export.table.toDrive(rights1993, "rights1993");
Export.table.toDrive(rights1994, "rights1994");
Export.table.toDrive(rights1995, "rights1995");
Export.table.toDrive(rights1996, "rights1996");
Export.table.toDrive(rights1997, "rights1997");
Export.table.toDrive(rights1998, "rights1998");
Export.table.toDrive(rights1999, "rights1999");
Export.table.toDrive(rights2000, "rights2000");
Export.table.toDrive(rights2001, "rights2001");
Export.table.toDrive(rights2002, "rights2002");
Export.table.toDrive(rights2003, "rights2003");
Export.table.toDrive(rights2004, "rights2004");
Export.table.toDrive(rights2005, "rights2005");
Export.table.toDrive(rights2006, "rights2006");
Export.table.toDrive(rights2007, "rights2007");
Export.table.toDrive(rights2008, "rights2008");
Export.table.toDrive(rights2009, "rights2009");
Export.table.toDrive(rights2010, "rights2010");
Export.table.toDrive(rights2011, "rights2011");
Export.table.toDrive(rights2012, "rights2012");
Export.table.toDrive(rights2013, "rights2013");
Export.table.toDrive(rights2014, "rights2014");
Export.table.toDrive(rights2015, "rights2015");
Export.table.toDrive(rights2016, "rights2016");