Assessing Usable Ground and Surface Water Level Correlation Factors in the Western United States

by

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ABSTRACT

The Western Continental United States has a rapidly changing and complex ecosystem that provides valuable resources to a large portion of the nation. Changes in social and environmental factors have been observed to be significantly correlated to usable ground and surface water levels. The assessment of water level changes and their influences on a semi-national level is needed to support planning and decision making for water resource management at local levels. Although many studies have been done in Ground and Surface Water (GSW) trend analysis, very few have attempted determine correlations with other factors. The number of studies done on correlation factors at a semi-national scale and near decadal temporal scale is even fewer. In this study, freshwater resources in GSW changes from 2004 to 2017 were quantified and used to determine if and how environmental and social variables are related to GSW changes using publicly available remotely sensed and census data. Results indicate that mean annual changes of GSW of the study period are significantly correlated with LULC changes related to deforestation, urbanization, environmental trends, as well as social variables. Further analysis indicates a strong correlation in the rate of change of GSW to LULC changes related to deforestation, environmental trends, as well as social variables. GSW slope trend analysis also reveals a negative trend in California, New Mexico, Arizona, and Nevada. Whereas a positive GSW trend is evident in the northeast part of the study area. GSW trends were found to be somewhat consistent in the states of Utah, Idaho, and Colorado, implying that there was no GSW changes over time in these states.

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INTRODUCTION

Water resources in the Western United States have become a growing concern among the inhabitants of the region. The Western U.S. has witnessed rapid population growth since the turn of the century (Hobbs, 2002). Population growth amid the Western U.S.'s arid and drought conditions have put a strain on available water resources (Anderson, 2005). Freshwater needed for sustaining a population makes up only 2.5% of the Earth's total water. Nearly 69% of freshwater is trapped in frozen form in glaciers and ice caps. This means that only about 0.78% of Earth's available water resources is usable freshwater (Shiklomanov, 1993). Due to projected increases in global temperatures, the Western U.S. expects seasonal changes in annual precipitation and snow melt events that directly affect water resource availability (NPS, 2017). Persistent changes in land cover, population growth and climate change will increase pressure on groundwater resources and are likely to cause permanent, non-recoverable depletion of water resources (Bell, 2018). Planning for the sustainable management of limited water resources demands exhaustive monitoring and analysis of water reserve changes.

Previous work has shown the connection between surface water and groundwater, though these are managed as separate resources in most states (Anderson, 2005). To improve understanding of the impact that environmental and social factors have on water resources, this study considers both ground and surface water together as a single resource. In this way we can better assess spatial regions that may be at risk to stressed water resources, as well as the most relevant influencers to that risk.

The current and impending water crisis demands a better understanding of the complex relationships between terrestrial and underground hydrological systems, land cover change, descriptive environmental landscape variables, and water user representative datasets. Only once causal and influential relationships in these systems are more fully understood will accurate implementation of conservative and sustainable use measures to prevent permanent underground aquifer damage be possible.

1.1 Literature

A few studies on Gravity Recovery and Climate Experiment (GRACE) derived groundwater change estimates data have been done, mostly in the context of groundwater recharge due to land cover change (Scanlon, 2008, Scanlon 2007, Scanlon, 2008(2)). Terrestrial Water Storage (TWS) depletion in the Colorado River Basin due to anthropogenic extraction and due to surface and soil moisture drought conditions have been observed (Scanlon, 2015). Many other authors have used GRACE's unique data set to estimate TWS and groundwater changes in the hydrological systems by supplementing GRACE data with surface water, soil moisture, snow and glacial estimates of liquid water equivalent, as well as others (Zaitchik, 2008, Forootan, 2013). Recent studies have also used the GRACE data to detect possible connections with LULC change and GSW change (Werth, 2017).

Little research was found on per-pixel trend analysis of the GRACE data and its correlation to descriptive land surface data (e.g. Land Surface Temperature (LST), Evapotranspiration, and Normalized Difference Vegetation Index (NDVI)). There is precedent in hydrological trend analysis, but neither on the scale nor the correlative scope of this project (Yue, 2004). These environmental variables undoubtedly have a significant association with the terrestrial and groundwater hydrological systems they depend on

(Srivastava, 2013, Niraula, 2015). There is minimal research on the association between groundwater systems and socioeconomic variables except in the realm of groundwater contamination and its impact on water users (Nahar, 2008, Ahamed, 2006).

Analyzing GSW changes with a per-pixel trend analysis against descriptive land surface data and water user's socioeconomic information is a research that can be expected to effectively analyze the complex interconnected relations of the basin's hydrological system, its landscape, and its water users. This project attempts to fill gaps in research by further exploring causal pathways to water resource change, while providing an assessment via a case study of the Western U.S.

1.2 Objectives

Ultimately, the goal of this project is to identify regions with significant correlation between environmental and social factors and GSW changes in the Western United States. To achieve the proposed goals, this study sets forth the following objectives:

1. Analyze the Gravity Recovery and Climate Experiment (GRACE) data alongside snow quantity (Snow Data Assimilation System, SNODAS) and soil moisture data (Global Land Data Assimilation System, GLDAS) to extract surface and groundwater changes between 2002 (GRACE launch date) and 2017 (GRACE decommission) in the Western United States.
2. Conduct a land-use/land-cover change analysis of the study area to determine specific areas of change in land cover classification that are significantly associated with ground/surface water change areas.

3. Explore the slope value trends of bio-physical and environmental parameters (e.g. Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Evapotranspiration (ET), etcetera) using spatio-temporal analysis techniques.
4. Explore the Rate of Change value trends of socio-economic parameters (e.g. Total Population, Population Density, Median Household Income, Property Values) using spatio-temporal analysis techniques
5. Examine the relations between the increasing and decreasing trends (slope) of the aforementioned bio-physical and environmental parameters and determine their relative significance, influence, and correlation to the increasing and decreasing trends (slope) of the ground/surface water storage changes.
6. Provide transformative options for future water management and policy changes for sustainable water use.

1.3 Results Benefits

Ground and surface water changes, as well as their influencing factors are extremely valuable information to federal and regional organizations wanting to take appropriate actions in their respective water resource management plans based on current and future needs and water resource influences. This study presents surface and ground water trends and changes spatially as well as temporally, thereby allowing policy makers and planners of water resource management at local scales to consider adopting/altering water use plans and regulations to facilitate the allowance of sustainable use of their water resource systems. This research also provides information on relevant positive or negative temporal trends of water resources spatially, enabling the determination of significantly affected regions of the Western U.S. as well as determining influential/causal factors of that change. Additionally, a new knowledge on the interaction between descriptive environmental parameters, census block scale socioeconomic changes, and their influence upon ground and surface water use and storage has been achieved.

MATERIALS AND METHODS

2.1 Study Area

The study area focuses on the western half of the United States, including the entire states of: Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming (Figure 1). The west coast of the United States, particularly California, has experienced substantial groundwater loss (Ojha, 2018). The total population of this region was estimated at almost 70 million people in 2006 (NWE, 2018) with the majority of this growing population residing in the south west portion of this region, causing additional localized strain on water and power resources. The study area covers a region of over 2.8 million square kilometers (Table 1) of consistently changing social characteristics (e.g. population, property value, income, etc.) and environmental characteristics (LULC, vegetation, climate, hydrology, etc.) (USDC, 2012). The regional scale of analysis provides an opportunity to evaluate the ground and surface water change of the region as a whole.

Table 1. Study Area

States	Area km^2
Arizona	295,234
California	423,972
Colorado	269,601
Idaho	216,443
Montana	380,831
New Mexico	314,917
Oregon	254,799
Utah	219,882
Washington	184,661
Wyoming	253,335

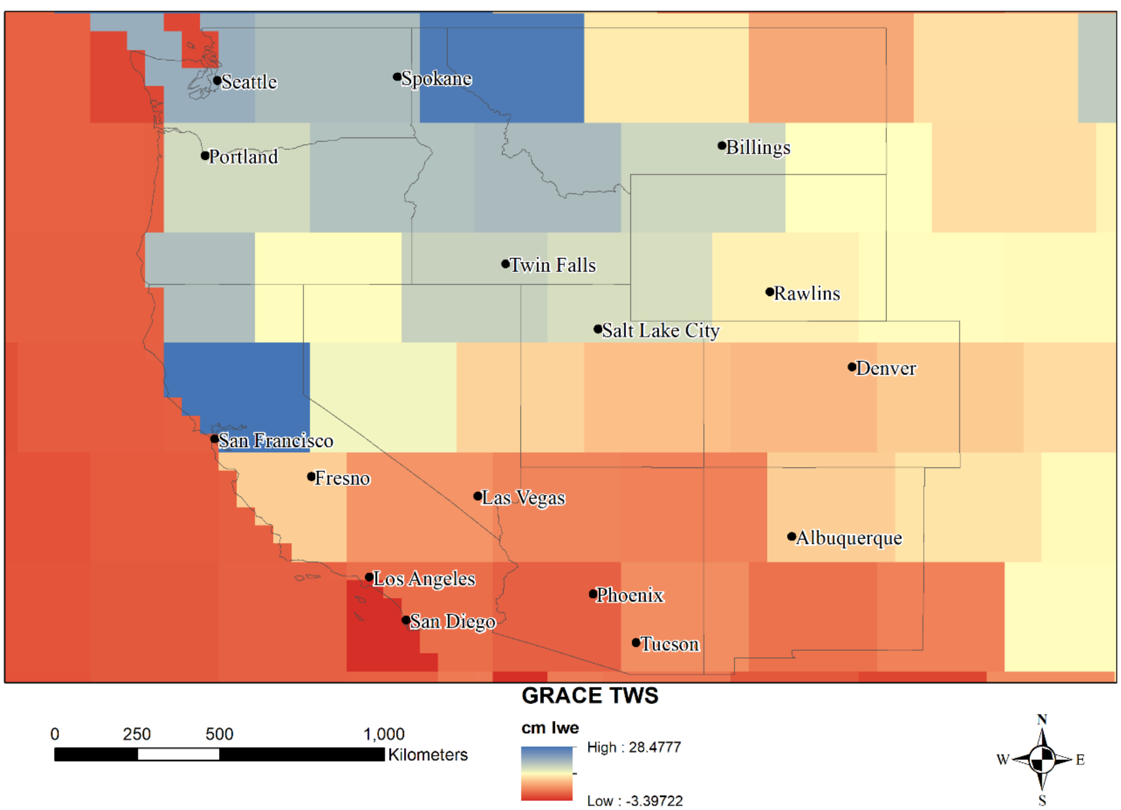

Figure 1. Study Area and GRACE Resolution

2.2 Datasets

2.2.1 Environmental - GSW

Ground and surface water changes were calculated from a series of data sets, incorporating Total Water Storage (TWS), Soil Moisture Storage (SMS), and Snow Water Storage (SNO). GSW was calculated as an annual average of millimeters of liquid water equivalent. These data sets are all free and publicly available through the National Aeronautics and Space Administration (NASA) and their affiliates (Table 2).

Table 2. GSW Isolation Datasets

Data	Source	Spatial Resolution	Temporal Granularity	Units	Temporal Coverage
GSW	Derived	0.5° x 0.5°	Monthly Average	millimeters liquid water equivalent	01/2004-06/2017
TWS	GRACE	0.5° x 0.5°	Monthly Average	centimeters liquid water equivalent	04/2002-06/2017
SNO	SNODAS	1km x1km	Monthly Average	millimeters liquid water equivalent	09/2003-01/2018
SMS	GLDAS	0.25° x 0.25°	Monthly Average	millimeters liquid water equivalent	1979-present

Note: 1 Hydrological datasets used to calculate monthly average Ground and Surface Water (GSW) changes, including: Total Water Storage (TWS), Snow Water Storage (SNO), and Soil Moisture Storage (SMS).Total Water Storage (TWS) is based on observations of the Gravity Recovery and Climate Experiment (GRACE) and provided through the level 3 product from NASA Jet Propulsion Laboratory (JPL) (Watkins, 2015). GRACE was a joint mission of NASA and the German Aerospace Center launched in March 2002 and decommissioned in October 2017. GRACE provided detailed measurements of Earth's gravity field and its changes by measuring the distance between the twin satellites as they orbited the Earth. The resulting gravity field measurements displayed the ways in which mass is distributed across the Earth and how that changes over time.

When interpreting GRACE TWS values, trends, and changes it is important to consider major water storage areas and their placement in the study area. One of the largest surface water bodies, the Great Salt Lake, lies in Utah. The Great Salt Lake covers an area of over five-thousand kilometers, and is an important consideration when deciphering GRACE TWS values in the study area. The other surface water lakes in this study area, Fort Peck Lake in Montana and Salton Sea in California, are a fraction of the size of Great Salt Lake. Known groundwater storage aquifer locations are also of particular use in analyzing and interpreting GRACE TWS data. In Figure 2 below are the U.S. aquifers as mapped by USGS (USGS, 2003). It is important to point out that many underground aquifers extend beyond their states borders while others are completely contained within them. For example, the Central Valley Aquifer in California is contained within the state, while the Basin and Range aquifers extend throughout the states of California, Nevada, Arizona, New Mexico, Utah, Idaho and Oregon.

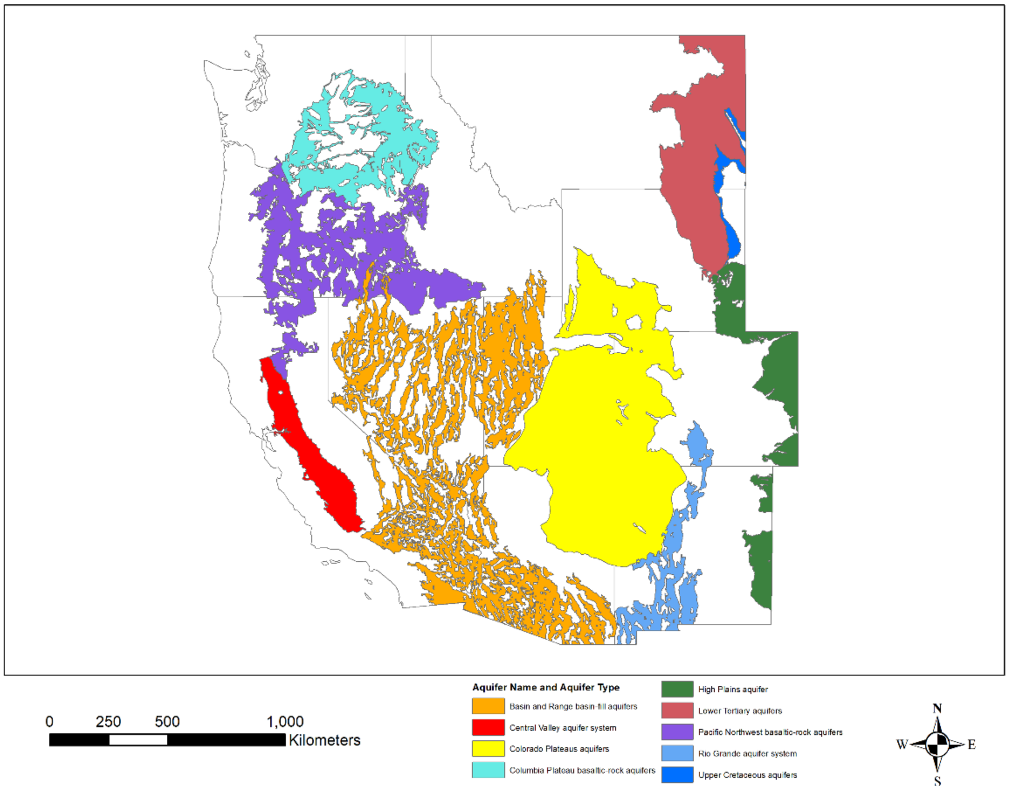

Figure 2. Principle Aquifers of the West U.S.

TWS change differences were provided in centimeters of liquid water equivalent from the 2002-2009 mean changes for the total temporal resolution of the GRACE satellite, from April 2002 to June 2017. The GRACE JPL provided monthly mass grids Global Mascons solutions have a native resolution of 3°x3° (Figure 1), which were multiplied by the land-grid-scaling factors also provided by NASA JPL, resulting in a finer 0.5°x0.5° resolution. An example of the GRACE data resolution for April 2002 is shown in Figure 1. The time period of the available snow water data to further isolate ground and surface water from TWS would not be available until January 2004, so the total temporal period used from the GRACE NASA JPL monthly mass grids is January 2004 to June 2017.

Soil Moisture Storage (SMS) was provided from the Global Land Data Assimilation System (GLDAS). GLDAS is a project through NASA that uses satellite and ground-based observations to input into complex land surface models producing multiple products for mapping Earth land systems. GLDAS soil moisture dataset provides measurements in millimeters of liquid water equivalent of SMS up to a depth of 2 meter (Rodell, 2018). Below this level, for this project's intents and purposes, we will allocate any water storage changes to Ground Water Storage (GWS). SMS from GLDAS is available at a spatial resolution of 0.25°x0.25° for the period of 1979 to present day. The dataset was downscaled through interpolation on a 0.5°x0.5° grid. SMS GLDAS data are retrieved for the overlapping period with snow and TWS data, hence, January 2004 to June 2017.

Snow Water Storage (SNO) was provided through the Snow Data Assimilation System (SNODAS), as part of the National Snow and Ice Data Center (NSIDC) The National Operational Hydrologic Remote Sensing Center (NOHRSC) developed SNODAS as a way to model and assimilate data in order to provide accurate estimates of snow cover to aid modeling of the hydrologic system. (Barret, 2003). SNO data from SNODAS was retrieved at a spatial resolution of 1kmx1km with the limiting temporal period of 28 September 2004 to 31 January 2018. The beginning of the study period would begin with the SNODAS initial data date of January 2004 and end with the GRACE terminal date of June 2017.

2.2.2 Environmental – MODIS

A variety of environmental variables and descriptors were obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS). These data sets include Land-Use Land-Cover (LULC), Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), and Evapotranspiration (ET) (Table 3). All of these data sets area free and publicly available from MODIS through NASA (MODIS, 2015).

Table 3. MODIS Datasets

Dataset	Source	Spatial Resolution	Temporal Granularity	Units	Temporal Coverage
LULC	MOD12 Q1	500 meters	Annually	17 Classes	2002-2013
LST	MOD11 C3	5600 meters	Monthly	Kelvin	2002-2017
NDVI	MOD13 A3	1000 meters	Monthly	Scaled 0 to 1	2002-2017
ET	MOD16 A3	500 meters	Annual	$kg/m^2/year$	2002-2016

Note: 2 Datasets acquired through MODIS, including: Land-Use/Land-Cover (LULC), Land Surface Temperature (LST), Normalized Digital Vegetation Index (NDVI), and Evapotranspiration (ET).

Table 4. LULC Reclassification

MODIS LULC Classification	Class Number	Study LULC Classification	New Class Number
Water	1	Water	1
Evergreen Needleleaf Trees	2	Forest	2
Evergreen Broadleaf Trees	3	Forest	2
Deciduous Needleleaf Trees	4	Forest	2
Deciduous Broadleaf Trees	5	Forest	2
Mixed Forest	7	Forest	2
Closed Shrublands	8	Shrub	3
Open Shrublands	9	Shrub	3
Woody Savannas	10	Grass	4
Savannas	11	Grass	4
Grasslands	12	Grass	4
Permanent Wetlands	13	Wetland	5
Croplands	14	Agriculture	6
Cropland/Natural Vegetation	15	Agriculture	6
Urban and Built-Up	16	Urban	7
Snow and Ice	17	Snow	8
Barren or Sparsely Vegetated	18	Barren	9

Note: 4 MODIS Land-Use/Land-Cover (LULC) native classification scheme and the reclassification to the Study LULC classification scheme.Land-Use Land-Cover was received from the MOD12Q1 data set. The data set has a temporal coverage of 2002 to 2013, the first and last of which were used for change detection to help correlate with our derived GSW data. Because of the National Land Cover Database (NLCD) would not have a LULC product more recent than 2013, MODIS LULC was utilized for this project. The native 17 classes of the LULC data set were reclassified to 9 classes which more accurately represented our area of focus (Table 4, Figure 3). The spatial resolution of this dataset is available at 500 meters, which would be resampled to our GSW 0.5°x0.5° resolution.

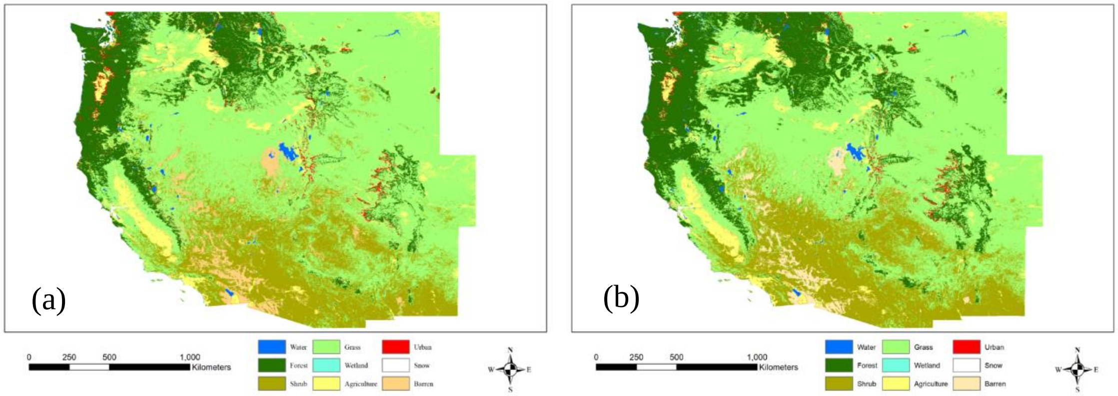

Figure 3. Land use land cover maps of the study area. (a) 2002 LULC map; (b) 2013 LULC map.

Land Surface Temperature (LST) (MOD11C3) dataset provides monthly average LST from 2002 to 2017. Monthly Average LST units in native Kelvin, were adjusted to Celsius. Monthly average LST was averaged to annual average LST to fit the GSW temporal resolution. The LST data has a spatial resolution of 5600 meters, which would be resampled to our GSW 0.5°x0.5° resolution.

Normalized Difference Vegetation Index (NDVI) is a commonly used indicator of the health of vegetation through the use of the red and near infrared spectral bands. NDVI is commonly scaled from -1 to 1 and also, as is the case with this dataset, from 0 to 1. 0 meaning low vegetative health and 1 meaning peak vegetative health. NDVI was retrieved from the MOD13A3 dataset which provides monthly averaged NDVI from 2002 to 2017. The spatial resolution native to the NDVI MODIS dataset is 1000 meters. The spatial and temporal coverage of the NDVI data was averaged and resampled to match the GSW 0.5°x0.5° annual average per pixel.

Evapotranspiration (ET) is a combined evaporation/transpiration used to describe the amount of water transferred from land to atmosphere. ET (MOD16A3) provides annual average ET from 2002 to 2016. ET is reported in kg/m²/year with a spatial resolution of 500 meters. The spatial resolution would be adjusted to the GSW 0.5°x0.5° spatial resolution.

2.2.3 Social – Census

Social descriptive variables were received from the U.S. Census Bureau from 2000 to 2016 at Census Block level. These data sets include Total Population (TP), Population Density (PD), Median Household Income (MHI), and property value, or the Value of Owner Occupied Units (VOOU). The difference between the years 2000 and 2016 divided by the temporal period between those two years was used to produce a Rate of Change (ROC) value for each of the data sets (Table 5). Each of these data sets was then resampled to the GSW 0.5°x0.5° spatial resolution. Total Population Rate of Change (TPROC) was derived from the TP at block level for each state, where the ROC was produced between 2000 and 2016.

Table 5. Census Datasets

Dataset	Spatial Resolution	Temporal Granularity	Units	Temporal Coverage
TPROC	Block Level	Annually	Total Population	2002-2016
PDCROC	Block Level	Annually	Total Population per Area	2002-2016
MHIROC	Block Level	Annually	USD $	2002-2016
VOOUROC	Block Level	Annually	USD $	2002-2016

Note: 5 Census datasets used in correlation with GSW datasets, including: Total Population Rate of Change (TPROC), Population Density Rate of Change (PDROC), Median Household Income Rate of Change (MHIROC), and Value of Owner Occupied Units Rate of Change (VOOUROC).

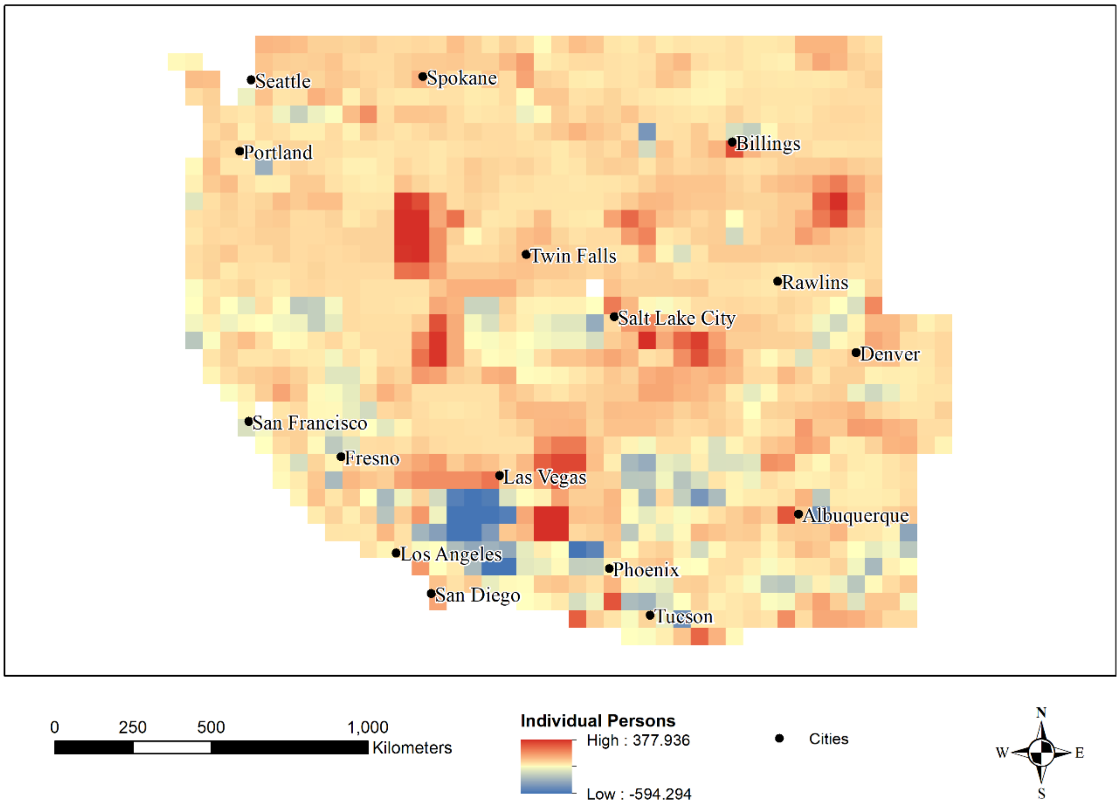

Figure 4. Total Population Rate of Change

Population Density Rate of Change was calculated from the TP block level data, by incorporating the area of each of the blocks to divide from the TP of that block to produce PD. PD changes were calculated between 2000 and 2016 and divided by the temporal coverage of the data to produce a PDROC file.

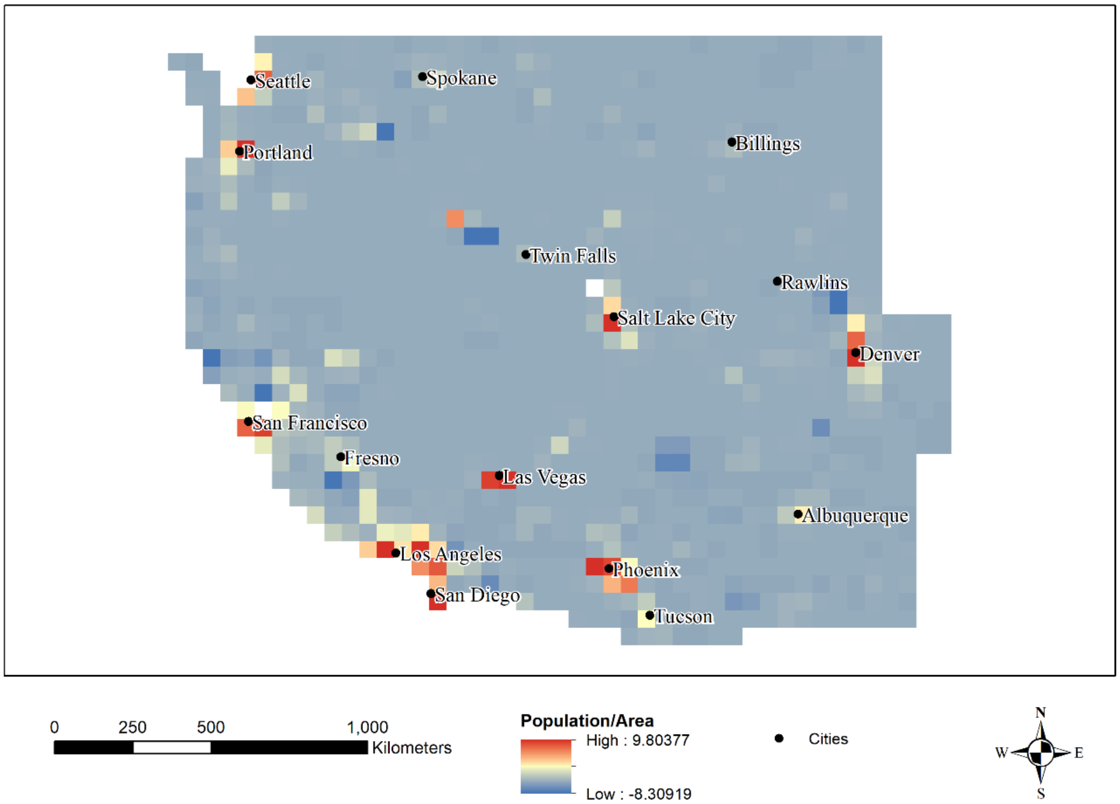

Figure 5. Population Density Rate of Change

Median Household Income Rate of Change (MHIROC) was calculated from the MHI provided at block level. The initial MHI difference was found from the first and last year of the available data, divided by the overall temporal coverage of the data, was utilized to produce the MHIROC.

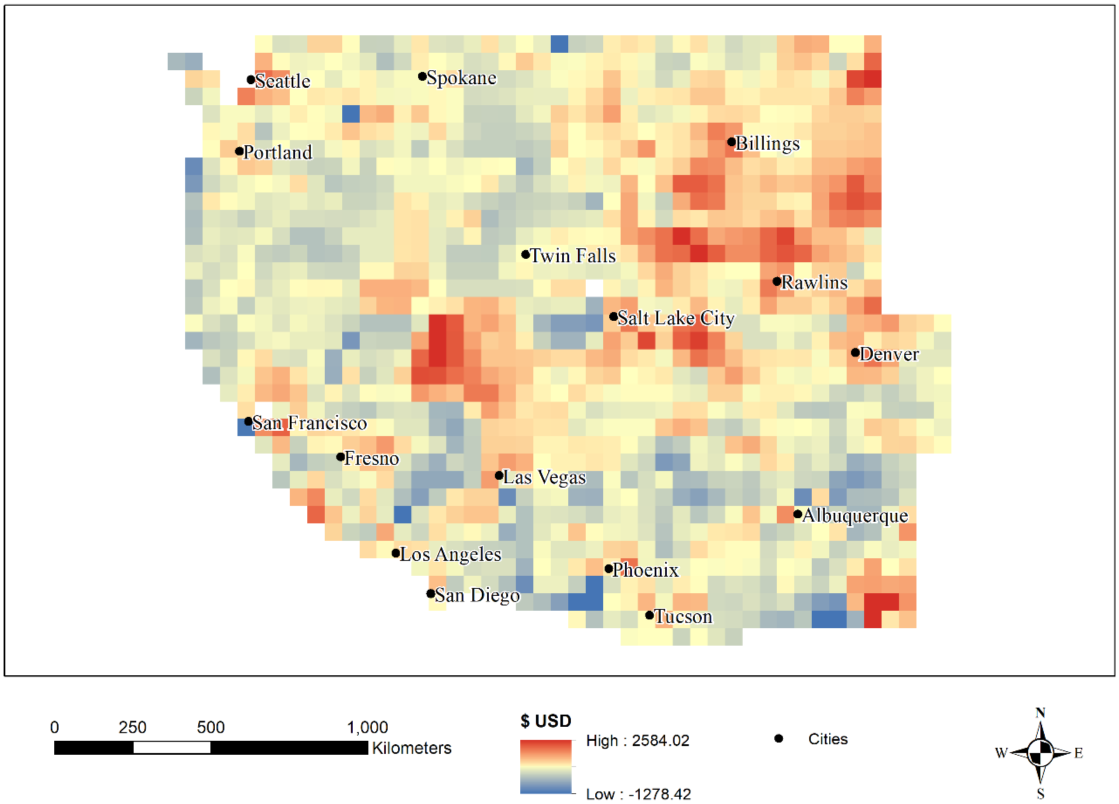

Figure 6. Median Household Income Rate of Change

Value of Owner Occupied Units Rate of Change (VOOUROC) was calculated from the census VOOU data to represent the property value at block level. The VOOU difference between 2000 and 2016 was divided by the total temporal coverage of the area to produce a VOOUROC.

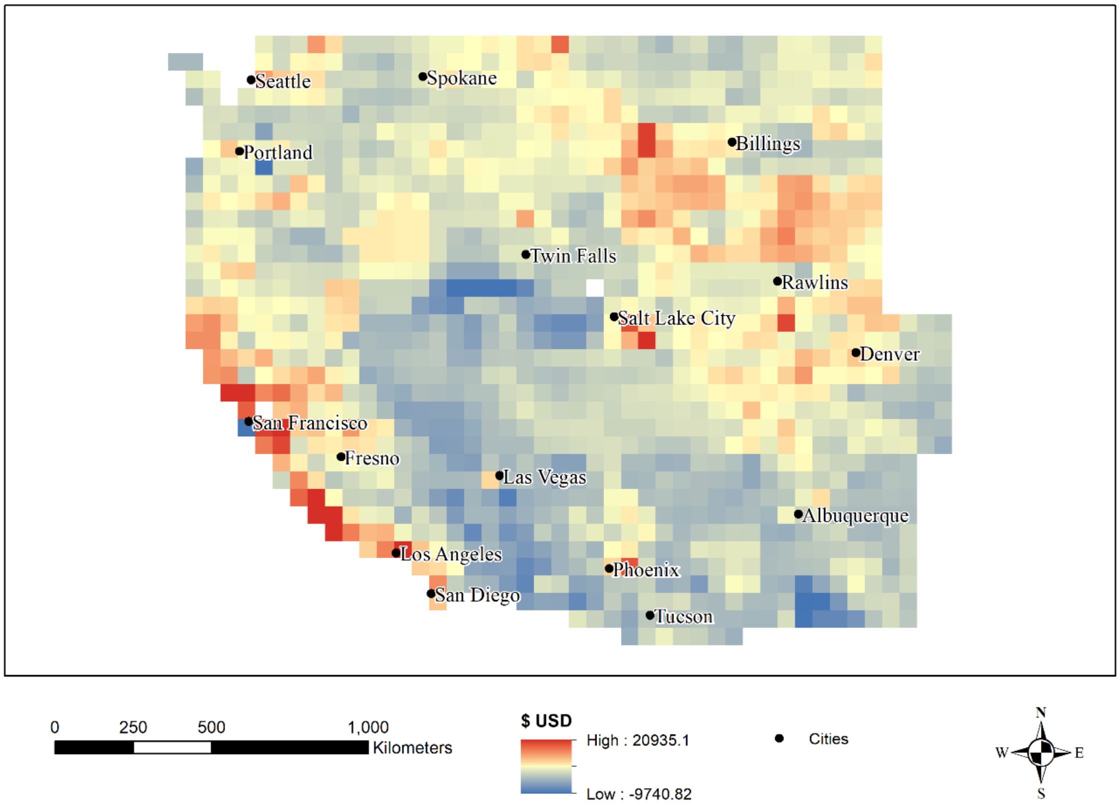

Figure 7. Value of Owner Occupied Unit Rate of Change

2.3 Methods

2.3.1 GSW Isolation

Ground and Surface Water (GSW) change was calculated based on the water storage equation:

$$\Delta TWS = \Delta SMS + \Delta SNO + \Delta SW + \Delta GW$$

where TWS is Total Water Storage, SMS is Soil Moisture Storage, SNO is Snow Water Storage, SW is Surface Water Storage, and GW is Ground Water Storage (Nimmo, 2005).

Due to the limitation of available surface water volume change data, the water storage equation was adapted to focus on fresh water sources for use and consumption, Ground and Surface Water (GSW) with the following equation:

$$\Delta GSW = \Delta TWS - \Delta SMS - \Delta SNO$$

where ΔGSW is Ground and Surface Water storage changes.

Because the water storage equation is applicable on all temporal scales, SNO and SMS changes were calculated as differences of monthly averages against the long-term mean over the study period. From these SMS and SNO monthly changes, average annual change was derived from the two data sets. GRACE TWS changes in centimeters of liquid water equivalent was converted to millimeters to fit SMS and SNO annual average storage changes. GSW was then isolated by subtracting annual SMS and SNO changes from annual total TWS changes.

Annual average GSW changes were reported from 2004 to June 2017 in millimeters of liquid water equivalent at a 0.5°x0.5° spatial resolution. All other data sets were adjusted to this spatial resolution, beforetesting for correlation. (Figure 8).

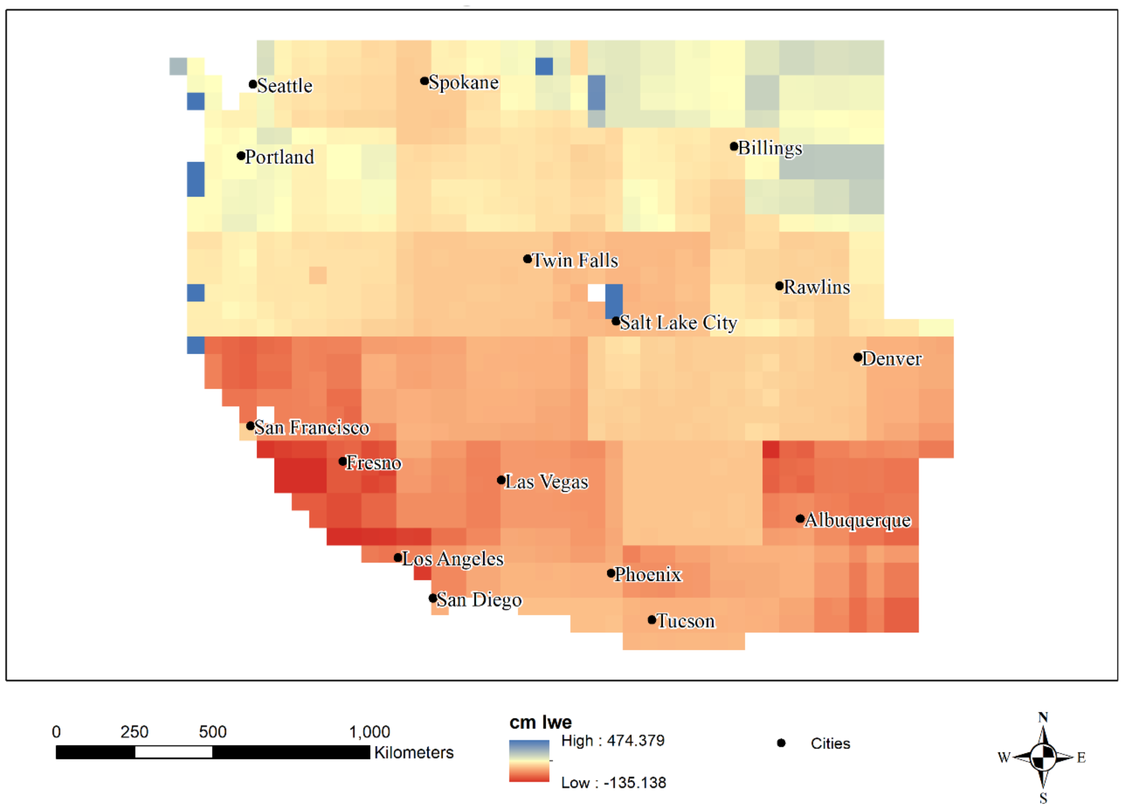

Figure 8. Ground and surface water mean changes

2.3.2 Time Series Significant Per Pixel Slope Analysis

The Mann-Kendall monotonic trend analysis method has recently been used in trend analysis of spatial data due to its powerful ability to detect trends, especially with hydrological data (Yue, 2002). The Mann-Kendall (MK) test's purpose is to test whether there is a monotonic trend over time. An upward or downward trend indicates that the variable tested consistently increases or decreases over time. The equation for calculating is as follows:

$$S = \sum_{k-1}^{n-1} \sum_{j-k+1}^{n} \boldsymbol{sgn}(x_j - x_k)$$

where S indicates the positive or negative trend, $x_j - x_k$ represents the possible differences where $j > k$, and $\boldsymbol{sgn}(x_j - x_k)$ is an indicator function that takes on values 1, 0, or -1 according to the sign of $x_j - x_k$ (Gilbert, 1987)

Utilizing the power of the Mann-Kendall monotonic trend analysis along with its associated rho significance test, significant linear slope trend maps were produced for the time series data sets, including: GSW, LST, NDVI, and ET. A 95% confidence interval was used in significance testing to ensure that only significant slope values produced would be included in the final correlation tests. The Mann-Kendall test was run on the native resolution of each of the LST, NDVI, and ET data sets, averaged, and resampled to GSW 0.5°x0.5° resolution. This results in an average significant per pixel slope of each of the MODIS time series data, LST, NDVI, and ET, at GSW resolution (Figure 9, Figure 10, Figure 11, and Figure 12).

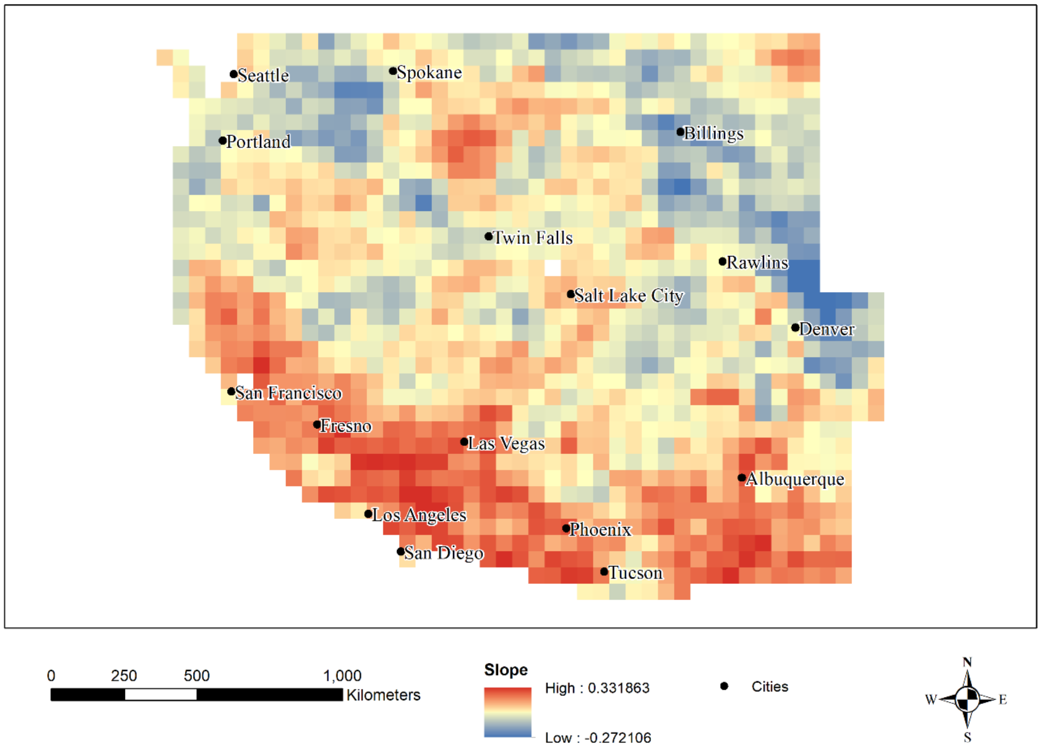

Figure 9. Land Surface Temperature Trend

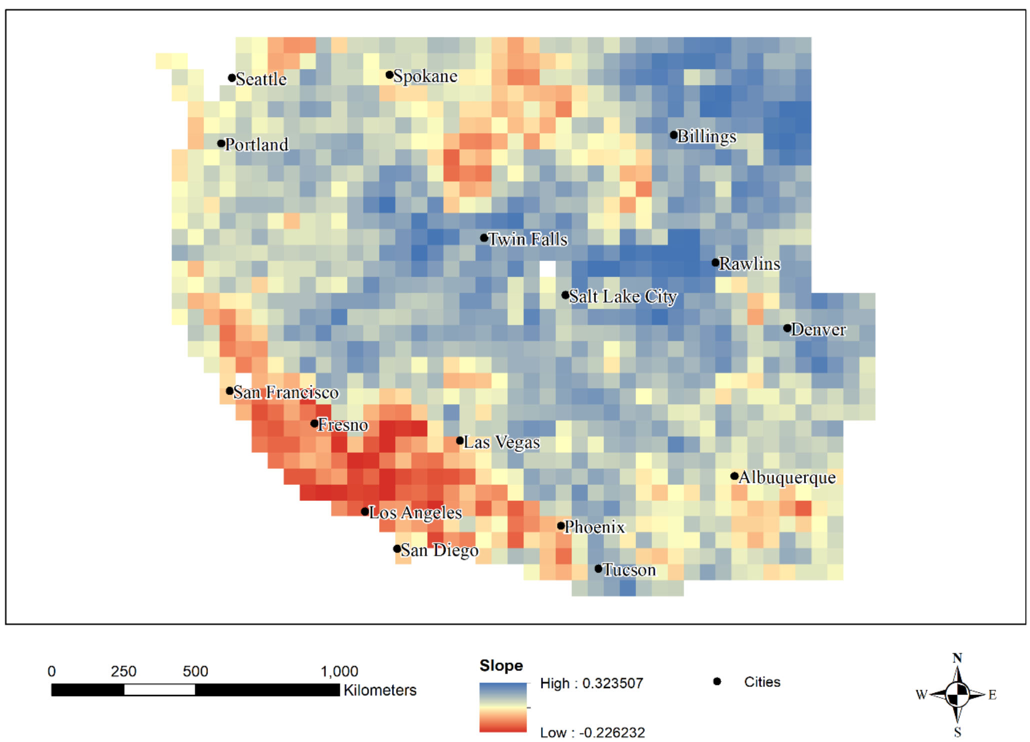

Figure 10. Normalized Difference Vegetation Index Trend

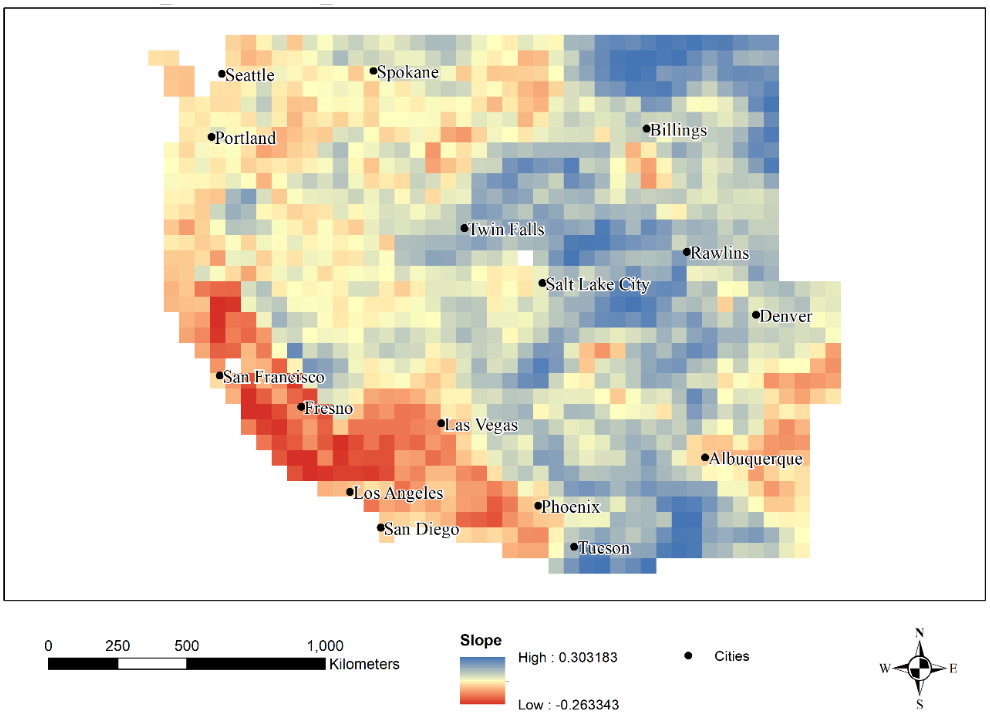

Figure 11. Evapotranspiration Trend

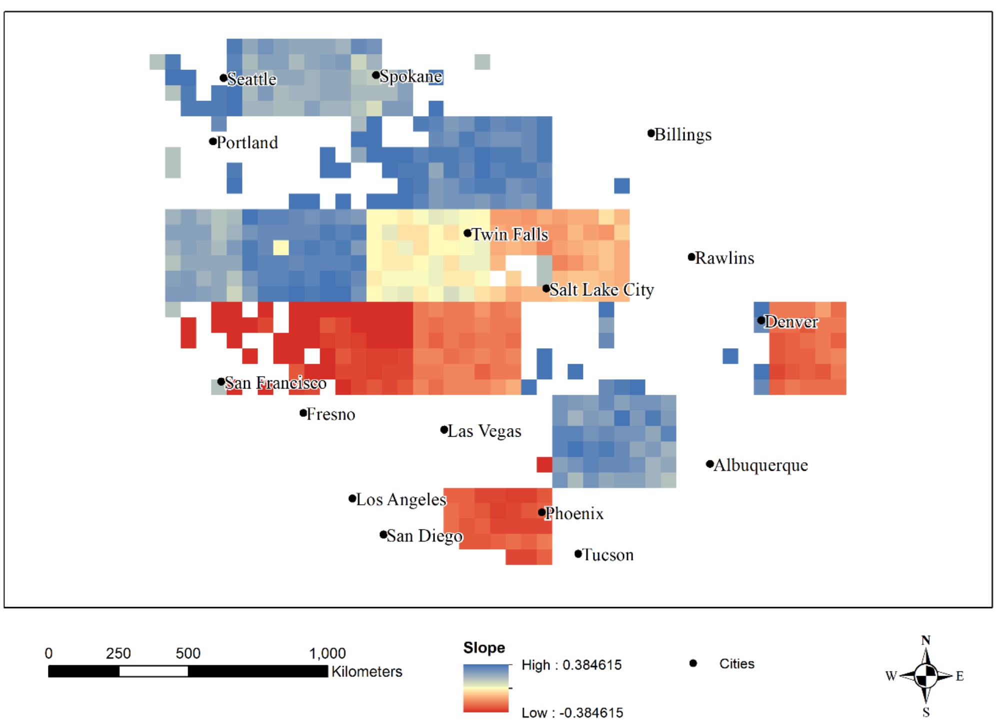

Figure 12. Ground and Surface Water Slope

Due to the coarse resolution and lack of significant slope values to cover the entirety of the study area, the correlation test of the environmental and social factors was run against GSW mean changes as well as GSW significant linear slope per pixel data.

2.3.3 LULC Change Detection

MODIS LULC scheme consists of seventeen classes. The native seventeen classification was reclassified to our nine classification scheme: Water, Forest, Shrub, Grass, Wetland, Agriculture, Urban, Snow, and Barren Land (Table 4).

A change detection analysis was performed between the start and end year of the data set (2002-2013). The area of each of the pixels was calculated in square kilometers, and the sum of the MODIS per GRACE pixels change was produced for each of the individual classifications: Water, Forest, Shrub, Grass, Wetland, Agriculture, Urban, Snow, and Barren. The area change for each class was calculated per GRACE pixel, with positive values representing kilometers of growth in the class, and negative values representing kilometers of removal in a class.

2.3.4 Correlations

Pearson Correlation has been proven to be a quality test to determine the spatial autocorrelation between separate spatial data sets (Chen, 2015). The Pearson Correlation is a measure of linear correlation between two variables, x and y, with values between positive and negative 1, where 0 is no correlation and 1 represents a total linear correlation. The equation for calculating the Pearson Correlation is as follows:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})}}$$

where n is the sample size, x_i and y_i are the individual sample points indexed with i, and $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, same for $\bar{y}$ (Pearson, 1895).

PC test were conducted on two levels. GSW mean changes were tested against the environmental and social variables previously discussed, while these same environmental and social variables were also tested against GSW slope values.

RESULTS

This study produced significant results in correlations of GSW mean and slope changes and environmental and social factors. Significant revelations in GSW trends were observed when the GSW trend was plotted for each state. Results of this study fall into three different topics: GSW Trends by State, GSW Mean Correlations, and GSW Slope Correlations.

3.1 GSW Trends by State

GSW trends were produced using the average monthly change in GSW calculated from GRACE TWS, SNODAS SNO, and GLDAS SMS. Monthly average values were extracted by state and plotted through the entirety of the study period for the GSW data, 012002-06/2017. Seasonal variations in GSW can be observed, and a linear trend line fit to display this data. The result is 11 GSW trends by state, with a linear trend line fit to the trends.

States with significant negative trends include California with a slope of -1.35, Arizona with a slope of -0.32, New Mexico with a slope of -0.70, and Nevada with a slope of -0.42. This generally equates to a liquid water equivalent loss of ~200mm in California, ~50mm in Arizona, and ~50mm in Nevada (Figure 13).

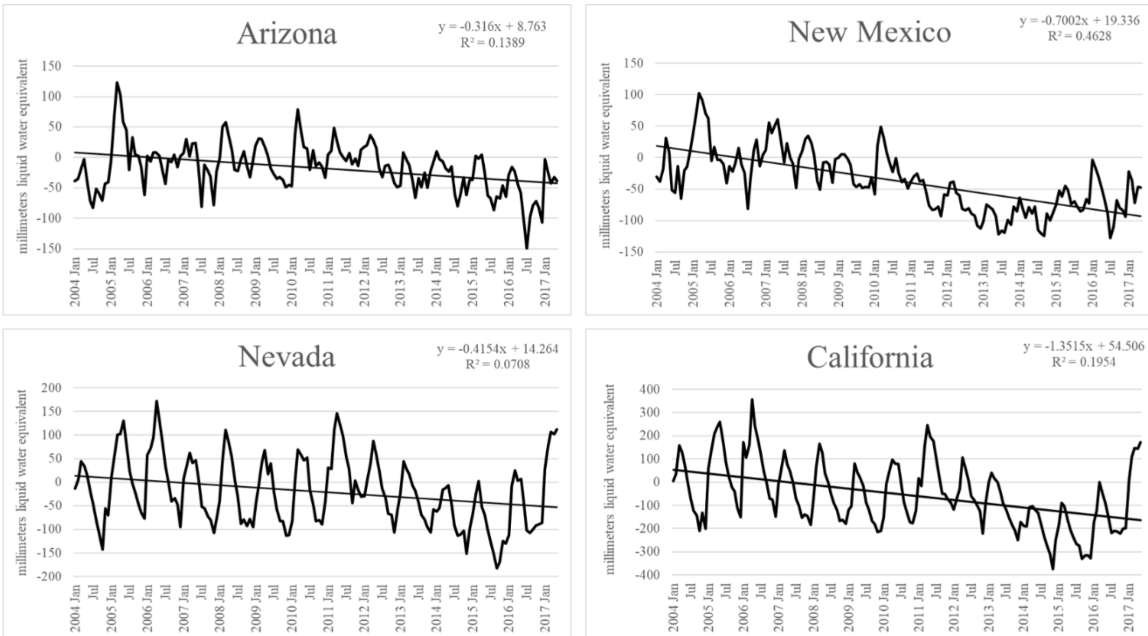

Figure 13. Negative GSW Trends

States with significant positive trends include Washington with a slope of 0.27, Wyoming with a slope of 0.46, Montana with a slope of 0.92, Idaho with a slope of 0.16, Oregon with a slope of 0.50. This can be noted as a gain of liquid water equivalent of ~50mm in Washington, over 50mm in Wyoming, ~150mm in Montana, ~25mm in Idaho, and almost 100mm in Oregon (Figure 14).

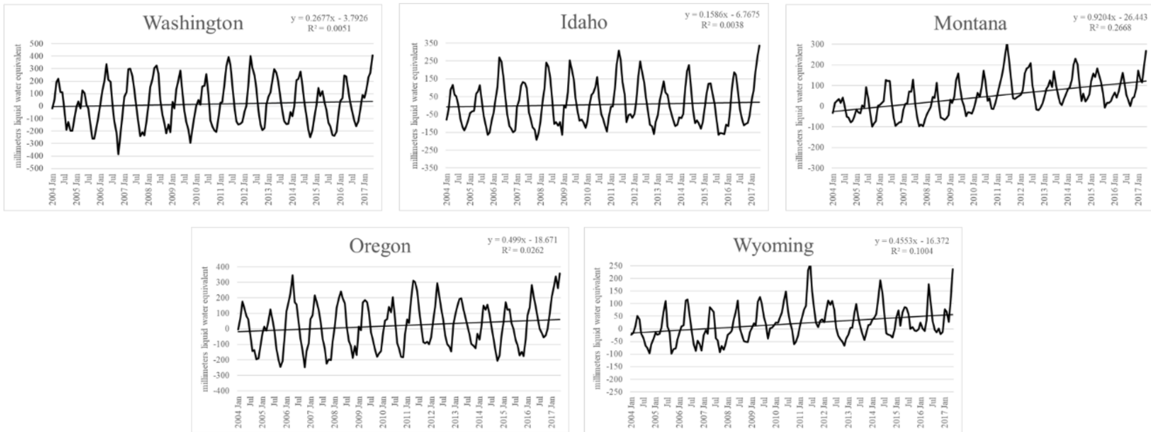

Figure 14. Positive GSW Trends

The remaining two states were found to have a near zero slope, with Utah reporting a slope of 0.02, and Colorado with a slope of 0.02. This should be considered a balanced GSW trend (Figure 15).

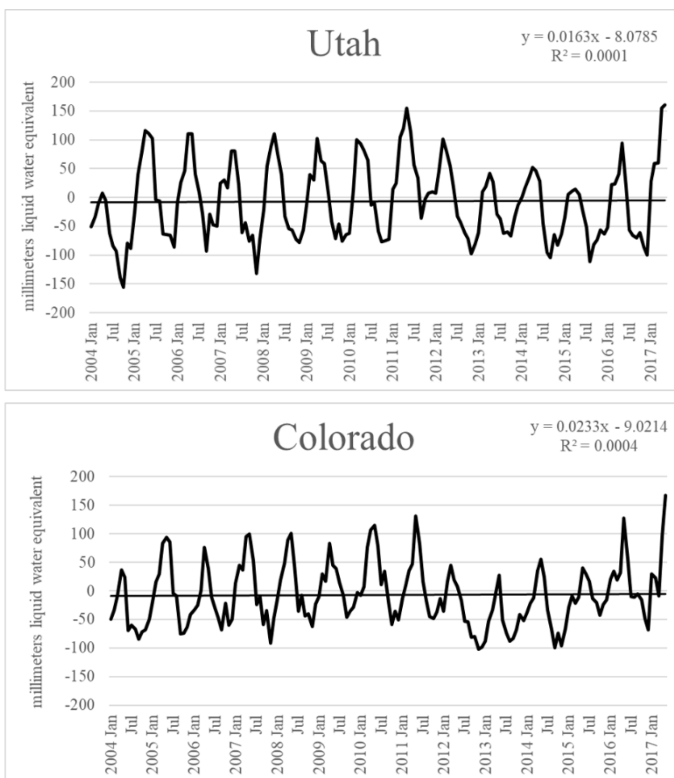

Figure 15. Near Zero Trends

States with negative slopes indicate that their ground and surface water resources have been declining, while states with positive slopes have been increasing. States with large negative slopes (California, Arizona, and New Mexico) may need to consider paying closer attention to water conservation efforts, considering the rate of change of ground and surface water is declining much more than others.

3.2 GSW Mean Correlations

GSW mean values were tested using the Pearson Correlation (PC) to determine the relationship between GSW mean values and the total sixteen other environmental and social data sets, as well as the extent and significance of that relationship. This test helps to determine which environmental and social factors may influence or be influenced by changes in GSW (Table 6).

Table 6 GSW Mean Correlation

GSW Mean Correlation	Pearson Correlation PC
LST	-0.425**
ET	0.303**
NDVI	0.290**
Shrub	-0.206**
Barren	0.188**
Forest	0.145**
Agriculture	-0.123**
TPROC	0.100**
VOOUROC	0.083**
PDROC	-0.078**
MHIROC	0.068*
Urban	-0.082*
Snow	0.092
Water	0.035
Grass	0.038
Wetland	-0.017

Note: 6 Ground and Surface Water mean correlation values tested against environmental and social factors. * Denotes correlation is significant at the 0.05 level. **Denotes correlation is significant at the 0.01 level.Of the sixteen data sets tested against the GSW mean change, LST, ET, NDVI, LULC change in Shrub, Barren, Forest, Agriculture, TPROC, VOOUROC, and PDROC were all significantly correlated to the GSW mean within a confidence interval of 99%. Further, MHIROC and LULC change in Urban was found to be significant within a 95% confidence interval.

The six highest positive significantly correlated variables tested were ET, NDVI, Barren, Forest, TPROC, and VOOUROC. This indicates a positive relationship, where an increase in any of these variables should observe an increase in GSW mean changes. Conversely, a decrease in any of these variables expects a decrease in GSW mean changes.

The four highest negative significantly correlated variables tested were LST, LULC change in shrub, agriculture and PDROC. This indicates a negative relationship between the variables, wherein an increase in any of the variables expects a decrease in GSW mean changes. A decrease in the value of these variables (LST, shrub, agriculture, and PDROC) would expect to experience an increase in GSW mean changes in that region.

3.3 GSW Slope Correlations

GSW slope values were tested using the Pearson Correlation (PC) to determine the relationship between GSW slope values and the total sixteen other environmental and social data sets, as well as the extent and significance of that relations ship. This test helps to determine which environmental and social factors may have an influence on GSW slopes (Table 7).

Table 7 *GSW Slope Correlation*

GSW Slope Correlation	Pearson Correlation PC
Snow	0.395**
Forest	0.291**
VOOUROC	0.214**
Shrub	-0.194**
LST	-0.154**
MHIROC	-0.154**
Wetland	-0.0151*
Urban	-0.104*
Agriculture	-0.094*
NDVI	-0.085*
ET	0.071
Barren	0.052
Grass	-0.049
Water	0.039
PDROC	-0.009
TPROC	0.000

Note: 3 Ground and Surface Water mean correlation values tested against environmental and social factors. * Denotes correlation is significant at the 0.05 level. **Denotes correlation is significant at the 0.01 level.

Of the sixteen data sets tested against the GSW slope LULC change associated with Snow, Forest, VOOUROC, Shrub, LST, and MHIROC were all found to be significantly correlated with GSW slope within a 99% confidence interval. Furthermore, LULC change in Wetland, urban, Agriculture, and NDVI were all found to be significantly correlated within a 95% confidence interval. Those datasets found not to be significantly related to GSW slope are ET, LULC change in Barren, Grass, Water, PDROC, and TPROC.

Positive significant correlations with GSW include LULC change class Snow, Forest, and VOOUROC. Significant negative correlations to GSW slope were found in LULC change class Shrub, LST, MHIROC, Wetland, Urban, Agriculture, and NDVI.

The Top three positive significant correlations were found in Snow change, Forest change, and VOOUROC. This indicates that an increase in any of these variables will also expect an increase in GSW slope, while a decrease in any of these variables finds a decrease in GSW slope.

The next three most strongly correlated variables (Shrub change, LST, and MHIROC) to GSW slope all have a negative relationship. Indicating that an increase in shrub lands, land surface temperature, or median household income would see a decrease in the GSW slope. While a decrease in any of these classes would expect an increase in GSW slope values.

DISCUSSION

GSW in the study area has significantly changed since 2004 as well as many of its environmental and social factors. The most significant negative changes in GSW occurred in the southwest portion of the study area, in the states of Arizona, California, and New Mexico, while the states of Oregon, Montana, Washington, and Wyoming experienced significant positive changes in GSW. Correlation testing between environmental and social variables reveals some of the causes of these trends, the most relevant being LST, NDVI, VOOUROC, Forest land changes, Shrub land changes, Agricultural land changes, and Urban land changes.

Population growth and its environmental impacts is a growing concern in the U.S. with LULC lands being transformed by the growing population. Changes from natural land covers (Forest, Shrub, Grass, etc.) to lands conducive to population growth like Urban areas, Agricultural lands, and Grasslands is common in regions with growing populations. LULC change is prevalent in disrupting the natural hydrology of an area by converting the land cover of the area, thereby altering the methods by which water systems behave (recharge, runoff, flows, etc.) (Nie, 2011). Although LULC changes are known to disrupt hydrological cycles, because of the complex interactions between different parts of the hydrological cycle, it can be difficult to determine direct spatial influencers. GSW mean changes correlation to LULC change, as seen in Table 6, indicate a strong relationship in Shrub land changes, Barren land changes, Forest land changes, Agricultural land changes, and Urban land changes. While the GSW slope correlation to LULC change seen in Table 7 indicates a strong relationship with Snow land changes, Forest land changes, Shrub land changes, Wetland land changes, Urban land changes, and Agricultural land changes.

Forests have been known to be positively associated with water resources (Welsch, 1991). An increase in forest resources would expect an increase in GSW resources, as proven by this study, while any deforestation would expect a decrease in GSW resources in the region associated with that forest loss. Shrub lands, which are commonly sparse of vegetation but not quite barren or desert lands, have been found to be negatively affecting water resources in studies (Spera, 2016). The finding of a strong negative relationship with shrub land change and GSW mean and slope indicates that regions with significant increase in shrub lands would negatively affect GSW changes by disrupting infiltration and percolation for ground water as well as total water volume in vegetation in that region. Shrub lands are also commonly known to become emergent in areas where deforestation has occurred. As discussed previously forest areas are positively correlated to GSW changes, therefore a loss of forested area to a shrub land cover would expect a negative relationship with GSW. Correlation tests reveal Agriculture land changes to have a negative relationship with GSW changes, indicating that a growth of Agricultural lands experiences a decrease in GSW changes in that region. Agricultural lands, as well as most any land cover change, significantly alters the surface/groundwater interactions, mainly through a change in groundwater recharge and an increase in irrigation of water resources. Agricultural changes in arid and semi-arid regions has been proven to be difficult to manage when considering water resources (Tanji, 2002). The arid regions of the southwest U.S. and the abundance of agricultural growth should cause concern and alarm for those involved with water resource management. Urban areas have been found to be negatively correlated with GSW changes, indicating that an increase in urban area would find a decrease in GSW. Urban areas consist of impervious surfaces, known for disrupting natural groundwater recharge into lower water aquifers.

Changes in social variables were found to be significant for TPROC, PDROC, MHIROC, and VOOUROC for GSW mean change correlations, while only VOOUROC and MHIROC were found to be significantly correlated to GSW slope. VOOUROC was found to be highly positively correlated with GSW slope, indicating that as GSW rises, so too does VOOUROC. VOOUROC was used in this study as an indication of property value, and is in units of U.S. Dollars. This would indicate that it is more costly to live where there is more access to usable water. GSW mean was found to be negatively correlated with PDROC, a measure of change of population density. This indicates that as more people move into an area and the population in that region becomes denser, the usable water in that area will decline.

Of the ten states in the study area, the states in significant decline and of most pressing concern in GSW resources are: Arizona, New Mexico, Nevada, and California

(Figure 12). It is important to consider the location of the groundwater aquifers as discussed previously and presented in Figure 2. One of the reasons California has such a strong trends and seasonality is due to the GRACE observation of the changes of the groundwater aquifers. California's Central Valley Aquifer is completely contained within the states boundaries, and has had significant loss to its storage during the study period. While the Basin and Range Aquifer spreads throughout the states of concern (Arizona, New Mexico, Nevada and California). California had the steepest negative GSW trend, equating to a loss of over 100 millimeters of liquid water equivalent during the study period. One of the major potential drivers of the GSW change is the high increases in population pressure (Figure 5) due to the growing cities of San Francisco, San Diego, and Los Angeles. This area is experiencing a population growth which is demanding increasing amounts of food and water to feed. This need for food demands more agricultural lands which will also demand more water resources. The collection of excessive population growth, agricultural growth, urban land growth, natural/forest land loss, and persistent drought conditions make California the area of most concern for GSW resources. California has already been observed experiencing surface deformation due to over extraction of groundwater resources (Chaussard, 2017). Much of the GSW loss that is caused by population density increases, particularly in California, can be attributed to groundwater over extraction.

GSW mean was most significantly correlated with three environmental variables, LST, ET, and NDVI. LST was found to be strongly negatively correlated with GSW mean, indicating that rises in temperature of the land would see a fall in the GSW values. Conversely, negative temperature trends were to see rises in GSW mean values.

ET and NDVI were found to have a positive correlation with GSW mean values. LST is known to have a pattern opposite of ET and NDVI, which explains the correlations of these data sets accurately (Deng, 2018). Rises is Land Surface Temperatures correlate to a fall in GSW, ET, and NDVI. Increases in NDVI, a measure of the health of vegetation, correlate to increases in GSW, implying that the healthier the vegetation in a region, the more usable water there is in that region. Research in the realm of changes in NDVI and its hydrological impact is known, with healthy vegetation often responding to that amount of available water (Aguilar, 2012). ET, a measure of evaporation and transpiration from vegetation into the atmosphere, can be understood in this context to have an intimate relationship with NDVI, LST, and GSW.

CONCLUSION

Hydrological systems and their influential relationships to the environmental and social factors are extensive and complex. Changes in usable water in the form of GSW are experiencing unprecedented changes due to environmental and social factors largely driven by human population growth and climate change. This research identified specific influential relationships between GSW changes and environmental/social factors since the turn of the century. The trend of the GSW changes in the study area have also been estimated for individual states. GSW trend analysis reveals strong negative trends in Arizona, California, and New Mexico, while strong positive trends were seen in Oregon, Montana, Washington, and Wyoming.

For both GSW mean and GSW slope, correlations with VOOUROC, LST, NDVI, and LULC change in deforestation were most significant. VOOUROC, NDVI and deforestation suggest a positive correlation in GSW changes, while LST observed a strong negative correlation to GSW changes.

The Primary causes of GSW changes in the western U.S. are over extraction from a growing population, LULC change caused by that growth, and climate changes. This study found that increases in total population, population density, property value, and median household income, land surface temperature, vegetative health, evapotranspiration, and LULC change in Forest, Shrub, Agriculture, and Urban were all correlated to GSW changes.

Some of the limitations of this study include the coarse resolution of the data sets and the period of available data. With finer resolution data sets more descriptive interactions between social and environmental variables and their relationship to water resources could be achieved. Further, finer resolution data sets allow for the risk assessment to be conducted on a smaller level than at just the state. A regional descriptive risk assessment may be able to provide more insight to areas that need more conservative water management techniques than others. LULC data beyond 2013 would provide additional insight into the extent of current state of LULC change, possibly allowing stronger correlation results.

In conclusion, the GSW problem in the western U.S., particularly in the southwest states of Arizona, California, and New Mexico, has been exacerbated by the negative affects a growing population has on its water resources. More sustainable water use policies, management, and planning becomes more pressing as projected population growth and climate change threatens ground and surface water levels through changes in seasonality and rising land surface temperatures. Based on the analysis results and findings of this study, it is recommended that water resource use, specifically in regions of high risk, be managed more conservatively and monitored more frequently. The detrimental effects caused by over extraction of groundwater and over use of surface water can cause irreversible stress and irreparable damage to underground water aquifers and surface watershed basins.

It is suggested that urban planners, city managers, and decision makers consider a review of their current policies and regulations that allow for urban development and land cover change, and incorporate a risk analysis of possible implications and risks in their usable water resources. Their policies need to incorporate not only the water needs of the population growing, but the land cover change, climate change, and status of past, current, and future projected usable water resource levels.

Additional research is needed in the relationship land cover change has with its water resources. Research incorporating finer scale LULC classifications could help to provide clearer insight on the interactions between LULC change and water resources. Follow up research using the GRACE Follow On mission to continue monitoring the state of our water resources would be beneficial to help extend GSW change trends beyond that of this study. The interaction of the hydrological system from atmosphere, to surface, to runoff, and down to percolation into the groundwater aquifer system is very complex. Only with further research and in depth analysis water resources and land-use/land-cover change can we begin to more sustainably and viably plan for sustainable population growth amid a changing climate.

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