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Analysis of Gravity Recovery and Climate Experiment (GRACE) Satellite-Derived Data as a Groundwater and Drought Monitoring Tool

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ANALYSIS OF GRAVITY RECOVERY AND CLIMATE EXPERIMENT (GRACE) SATELLITE-DERIVED DATA AS A GROUNDWATER AND DROUGHT MONITORING TOOL

by

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ANALYSIS OF GRAVITY RECOVERY AND CLIMATE EXPERIMENT (GRACE) SATELLITE-DERIVED DATA AS A GROUNDWATER AND DROUGHT MONITORING TOOL

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This research compares Gravity Recovery and Climate Experiment (GRACE) groundwater storage (GWS) and root zone soil moisture (RZSM) percentiles to measured data, other drought indicators (DIs) and indices, and stakeholder observations for the purpose of assessing the feasibility and usefulness of these products to detect drought conditions. GRACE percentiles were directly compared to historic groundwater percentiles at 89 Nebraska well locations. Spatial time-series correlations over CONUS were performed between GRACE GWS and RZSM and the U.S. Drought Monitor (USDM), Standardized Precipitation Index (SPI), and soil moisture parameters from several North American Land Data Assimilation System (NLDAS) models. A survey of stakeholder observations during a 2016 flash drought event centered on Montana, Wyoming, South Dakota, and Nebraska was also compared to GRACE percentile data to analyze drought onset timing, geographic coverage, and severity.

Overall the results show GRACE GWS has similar spatial and temporal agreement over the well period of record, and generally has the expected negative correlation relationship with observed groundwater, but it does not accurately reflect historic percentiles in Nebraska. GRACE GWS and RZSM have moderate correlation

with USDM, and high correlation with SPI, and NLDAS models over the entire U.S. with notable regional and seasonal patterns. SPI accumulation period also plays an important role in correlation strength for both RZSM and GWS with the best agreement seen at 3-month and 12-month accumulation periods, respectively. GRACE RZSM time-series data closely matches stakeholder observations of decreasing soil moisture availability, while observations of decreasing water levels were not as closely matched by GWS. When analyzed as an average over all responding zip codes, RZSM showed an early warning trend up to six weeks prior to observed reports. These results indicate GRACE percentiles are promising drought indicators that can be used as a monitoring and early warning system by decision makers.

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Table of Contents

List of Multimedia Objects

CHAPTER 1 – INTRODUCTION

1.1 Motivation

Drought monitoring is a complex, but important, task in the study of weather and climate and in reducing societal vulnerability to drought. Economic damages from droughts have risen in the past decades and drought impact is estimated in billions of dollars every year in the United States (Smith & Katz 2013, Wilhite, 2000). Depleted groundwater and soil moisture are some of drought's most severe effects, causing water shortages and reduced crop yield (Denmead et al. 1962). Remote sensing and modeling of drought's impacts can help quantify through objective measures the extent and severity of drought, identify the timing of drought onset and conclusion, and determine the frequency of drought over individual regions.

The National Aeronautics and Space Administration's (NASA) Gravity Recovery and Climate Experiment (GRACE) mission has produced groundwater storage and root zone soil moisture drought indicators (DI) based on satellite gravitational measurements assimilated into land surface models. These products are calculated as a percentile of the historic mean (see section 1.3) and thus are directly comparable with other percentile-based DIs. The monitoring of the severity and timing of droughts through tools like GRACE DIs helps in providing decision makers with improved, more timely information to mitigate and respond to this natural disaster.

This research assesses these GRACE percentile DI products by comparing them against measured data, other known DIs and indices, and the observations of drought by stakeholders during a notable, recent drought event. This type of assessment is necessary for several reasons. First to determine the accuracy of the GRACE DIs to represent historic groundwater or soil moisture conditions through the percentile method. The second is to evaluate the usefulness of GRACE percentile products as DIs. Although precise estimates of groundwater and soil moisture may have inaccuracies, they still have value in the relative differences depicted between current and historical conditions. This is because the drying and wetting trends, that may not accurately reflect historic percentiles, are still apparent in GRACE DIs for drought events. For example, an event that GRACE characterizes as dropping from 80% soil moisture to 31% soil moisture (edge of D0 drought as designated by USDM) may not mean current soil moisture is ranked historically in the bottom 31% of years, but the rapid drying clearly indicates a significant effect. The comparison to other DIs can show GRACE's spatial and seasonal strengths and weaknesses because of the relatively known strengths and weaknesses of the more extensively studied DIs.

Currently, spatially continuous, long-term soil moisture datasets in the U.S. are modeled. These models help in assessing dryness, however the associated uncertainties in accuracy may lead to choosing other DIs to use to determine drought extent. Sparse groundwater observations and the resulting spatial interpolations are the only way to quantify groundwater levels, which are very important to agricultural producers especially in times of long-term drought. GRACE percentile datasets may help close this gap in soil moisture and groundwater data. An increase in soil moisture estimate accuracy and a spatially continuous groundwater dataset would be an invaluable resource for stakeholders and drought specialists alike.

1.2 Drought Monitoring Background

Several decades of research have yielded different definitions for drought (Wilhite 2000). Although they are all connected, different types of droughts can vary by length and affect local resources differently. In general, meteorological drought is defined as abnormal periods with low or no precipitation. Hydrological drought deals with the effects of precipitation working through reservoirs, streamflow, and groundwater. Agricultural drought is how crops respond to increased heat stress and lack of water availability in the soil. Finally, socioeconomic drought is associated with economic supply and demand of goods, such as water and agricultural products, which are heavily affected by meteorological, hydrological, and agricultural droughts (Wilhite and Glantz 1985). All of these drought types have water in common, and thus monitoring water is a pivotal aspect to study for all of these sectors (Tallaksen 2004).

Drought monitoring using objective and subjective assessments of weather, hydrology, agriculture, and human responses is an important part in the goal of successfully mitigating and responding to drought effects. The widespread use of remote sensing systems, in acquiring meteorological, hydrological, and vegetation health data, allows for multiple high spatial resolution, multi-faceted resources to quantify and respond to drought.

The first quantitative drought indices appeared early in the 20th century as Munger’s Index and Kincer’s Index (Heim 2002). These indices measured the period of time without a specific amount of precipitation. Because precipitation is a highly variable quantity, any fixed amount of precipitation would not be sufficient for all regions. The mid-20th century saw more drought indices evolve to include more than just precipitation, and specifically analyzed variables necessary for agricultural and hydrological impacts (Heim 2002). In 1965, Palmer developed the Palmer Drought Severity Index (PDSI) that accounts for temperature and precipitation in a water balance model (Palmer 1965). This index was effective at identifying long-term droughts, and accounted for several variables previously ignored, however it lacked a high degree of comparability between regions and did not account for snow or ice. The next largest innovation in drought monitoring was in 1993, with the creation of the Standardized Precipitation Index (SPI), which determines precipitation surpluses or deficits in terms of anomalies from normal, allowing uniform calculation in different regions (McKee et al. 1993). While SPI deals very well with meteorological drought, it has limitations in identifying hydrological and agricultural droughts (World Meteorological Organization 2012). Additionally, climate-based drought indices are based on weather station data (sometimes interpolated to a uniform grid) which are far less dense in remote areas. In contrast, satellite-based indices have continuous, equal coverage of the entire area of interest.

Modelling and remote sensing have recently become driving forces in drought monitoring with their ability to look at the large-scale effects of drought. The Normalized Difference Vegetation Index (NDVI) was one of the first to make use of remotely sensed imagery as a drought tool (Rouse et al. 1974). Using the normalized differences in spectral reflectance, vegetation health, often linked to water availability, is assessed. Hybrid drought indices such as the Vegetation Drought Response Index (VegDRI) (Brown et al. 2008) use the combined power of remote sensing and observed data to assess drought impacts on vegetation. NLDAS soil moisture (Xia et al. 2012a, Xia et al. 2012b), often used to identify drought events, similarly uses observed data to model soil moisture at high resolution.

Groundwater, an important resource for agriculture and urban centers, is currently monitored based on individual well measurements across the country, and usually done at the natural resource district, state, or aquifer scale. The varying groundwater depths, terrain, aquifer type, and observation density all contribute to a sparse set of groundwater data for the United States. Some modeled data based on these observations are also available, but many are focused at the regional level.

Because of the impacts of drought on state and federal resources, the National Oceanic and Atmospheric Administration (NOAA), the U.S. Department of Agriculture (USDA), and the National Drought Mitigation Center (NDMC) have created a weekly drought monitor map based on several climate and satellite-based DIs and indices, other in situ measurements and drought expert input from across the United States (Svoboda et al. 2000). Because drought has no formal, or quantitative definition, U.S. Drought Monitor (USDM) authors rely on a combination of objective drought indices as well as subjective expert analysis and regional and local impact reports to create comprehensive weekly maps of hydrological and agricultural drought conditions for the conterminous U.S., Alaska, Hawaii, and Puerto Rico.

1.3 GRACE Background

Earth's gravitational changes are measured by the GRACE two-satellite system in an orbit at an 89.5° inclination, ~500km altitude, in which the satellites are ~220km apart. A microwave-ranging instrument aboard the satellites measures changes in distance between the two satellites from which it can create maps of Earth's changing gravity field. The primary cause of these changes in gravity are the fluctuations of water mass on Earth (Tapley et al. 2004). The GRACE satellite system has provided measurements of gravity changes for the entire globe from April 2002. In October 2017, one of the satellites suffered a battery failure, causing the mission to conclude (NASA, 2017). GRACE-Follow On (GRACE FO) was launched in May 2018 and promises to provide the same hydrologic products as the original mission, while testing several measurement methods for higher accuracy and precision.

The satellite data are processed at three centers that include the University of Texas Center for Space Research (CSR), the GeoFroschungsZentrum Potsdam (GFZ), and NASA's Jet Propulsion Laboratory (JPL). Each center has a unique processing algorithm, but with the same main calculations and characteristics. GRACE observed estimates of total water storage (TWS) are produced at monthly intervals at a spatially limited 150,000 km^2 horizontal resolution (Rowlands et al. 2005, Yeh et al. 2006). The processed GRACE TWS is a single value comprised of soil moisture, vegetation, surface water, ice, snow, and groundwater. It represents the entire vertical column at and below the surface of the Earth. Through several studies, it has been shown that GRACE data can be effectively integrated into land surface models (LSM) in order to disaggregate components of total water storage changes (TWSC) (Wahr et al. 1998). This disaggregation is done by subtracting modeled soil moisture and snow water equivalent from GRACE TWS. Most estimates assume vegetation and surface water to be terms small enough to negate. GRACE data have been successfully assimilated into LSMs and disaggregated into terms of snow water equivalent (SWE) (Niu et al, 2007) that improved estimates of hydrologic state and fluxes (Su et al. 2010 and Forman et al. 2012), root zone soil moisture (RZMC) (Wahr et al. 1998), and groundwater storage (GWS) (Rodell et al. 2007).

The GRACE TWS product has been assimilated into the Catchment Land Surface Model (CLSM) (Koster et al. 2000, Ducharne et al. 2000) and the disaggregated data is used in this research. This method increases spatial and temporal resolutions and disaggregates TWS into some of its component parts (groundwater, soil moisture, and snow water equivalent). The CLSM is configured with a grid centered over the conterminous United States similar to the North American Land Data Assimilation System (NLDAS) (Mitchell et al. 2004), and simulated with NLDAS-2 meteorological and energy flux forcing data (Xia et al. 2012a, Xia et al. 2012b)

The GRACE assimilated CLSM takes forcing data inputs (precipitation, solar radiation, temperature, wind, humidity, and pressure) and integrates GRACE TWS into the model using an Ensemble Kalman smoother (Zaitchik et al. 2008, Kumar et al. 2016). Groundwater and soil moisture have been modeled by CLSM during the 1948-2016 period using historical observations as inputs. The GRACE data assimilated (DA) model products are then calculated as a percentile of the historic conditions and will be assessed for their usefulness as drought indicators.

GRACE TWS that was disaggregated into groundwater and assimilated into model simulations was previously evaluated against non-assimilated, open loop model simulations on a basin scale across the United States (Zaitchik et al. 2008, Houborg et al. 2012). Zaitchik et al. found small, but significant ($\alpha < .05$) increases in correlations for three out of five basins (Mississippi, Ohio-Tennessee, and Missouri), with another basin (Red-Arkansas/Lower Mississippi) seeing significant improvement at $\alpha < 0.10$ when compared to the non-assimilated simulation. Houborg et al. found significant ($\alpha < .05$) improvement for three basins (Great Basin and Colorado, Upper East Coast, and Arkansas-Red/Lower Mississippi), while two basins (Missouri and California) saw statistically significant ($\alpha < .05$) skill decreases.

This research assesses the relationship between measured groundwater levels and GRACE groundwater percentiles and compares GRACE percentiles to other DIs and indices. A GRACE-based DI percentile approach was first examined by Houborg et al. in 2012 in order to translate GRACE-assimilated products such as surface soil moisture, root zone soil moisture, and groundwater storage into drought indicators consistent with the U.S. Drought Monitor. While inaccuracies, measurement and computational errors, and modelling deficiencies can produce notable differences between the absolute GRACE soil moisture and groundwater estimates and observed data, a percentile approach for the datasets provides historical context and allows relative comparisons between the records to assess the general anomalies that are represented. While percentile datasets are sensitive to the total dataset time period and comparing percentile datasets with different spin-up periods can result in disagreement, the general benefit of spatially independent historic context is critical when mitigating and making decisions in drought events. This study analyzes the comparison between GRACE groundwater percentiles and long-term United States Geological Survey (USGS) groundwater records as well as between GRACE groundwater percentiles and shorter-term well records from the Nebraska Real-time Monitoring Network (RTMN). The relationships between GRACE percentiles and the U.S. Drought Monitor (USDM) (Svoboda et al. 2002), Standardized Precipitation Index (SPI), and the North American Land Data Assimilation System (NLDAS) modeled soil moisture are also studied.

CHAPTER 2 – DATA AND METHODOLOGY

2.1 Data Processing and Descriptions

As the GRACE satellites launched in March 2002, actively retrieving data since April 2002, all comparisons are made with the same start date of the first week of April 2002. However, due to the data not being available when this research was conducted, SPI and NLDAS data comparisons only extend to the end of 2012, whereas groundwater well and USDM comparisons were extended to the end of 2016.

2.1.1 GRACE Percentile Data

This study uses two GRACE percentile products, groundwater storage (GWS) and root zone soil moisture (RZSM). These data are produced weekly at 0.125° spatial resolution (approximately 13.8 x 13.8 km) and the time period of April 2002 – December 2016 is used. These data are in a raster format over the continental United States. Each cell in the raster contains a single percentage value, '0' representing the driest historical condition for that location, and '100' representing the wettest condition. Each of the cells in these data-assimilated percentiles from 2002-2016, calculated from on the historical model data, on average range from 0.8 – 99.8% for RZSM and 3.2 – 97.3% for GWS. This large range indicates that both GWS and RZSM products capture nearly all variability of the historic dataset, and adequately represent trends during this time period. The original data are processed by clipping the spatial extent to match the exact boundaries of the continental U.S. (the raw data extended well into Canada and Mexico) as to match the coverage of the other datasets.

Then, these data are copied and separately processed according to the temporal and spatial resolution of the data to which it was being compared. A set of raster data is resampled to match the larger spatial resolution of SPI (25 x 25 km) and NLDAS (20.2 x 20.2 km) rasters using the nearest pixel resampling method. The SPI matching dataset had weekly values which are averaged to monthly values using ArcGIS python scripting. Finally, for the USDM comparison, GRACE percentiles were reclassified into their respective drought levels as given by Table 1.

Table 1 – U.S. Drought Monitor drought severity levels and equivalent percentiles to compare to objective drought indices (Svoboda et al. 2000)

DROUGHT LEVEL	**PERCENTILE**
No Drought	31 - 100
D0 – Abnormally Dry	21 - 30
D1 – Moderate Drought	11 – 20
D2 – Severe Drought	6 -10
D3 – Extreme Drought	3 - 5
D4 – Exceptional Drought	0 -2

2.1.2 Groundwater Wells

To assess GRACE GWS accuracy, values were compared to measured groundwater well levels across the state of Nebraska. While each well represents only a single point compared to the GRACE cells of about 190.44 km^2 in area, assessing the two percentile levels and trends can begin to show what level of accuracy the GRACE DI has.

Two well datasets are used in this research, the United States Geological Survey (USGS) daily groundwater data and the Nebraska Real-Time Monitoring Network (RTMN) daily groundwater data.

The USGS keeps a collection of continuously reporting groundwater wells across the country (USGS 2016). In Nebraska, USGS maintains 33 of these wells (Figure 1) with relatively long-term, daily historical records. These well sites measure water levels as distance from the surface station at least once per day and automatically store and report the level. This provisional data is put through USGS quality assurance to ensure consistent and accountable measurements. These wells were selected because their historical records dating back to at least 1999, maintaining a historical record longer than the GRACE record. While aquifer type certainly does impact the well level responses to drought, selection was not based on this characteristic because of the already small sample size with the stipulation of record length.

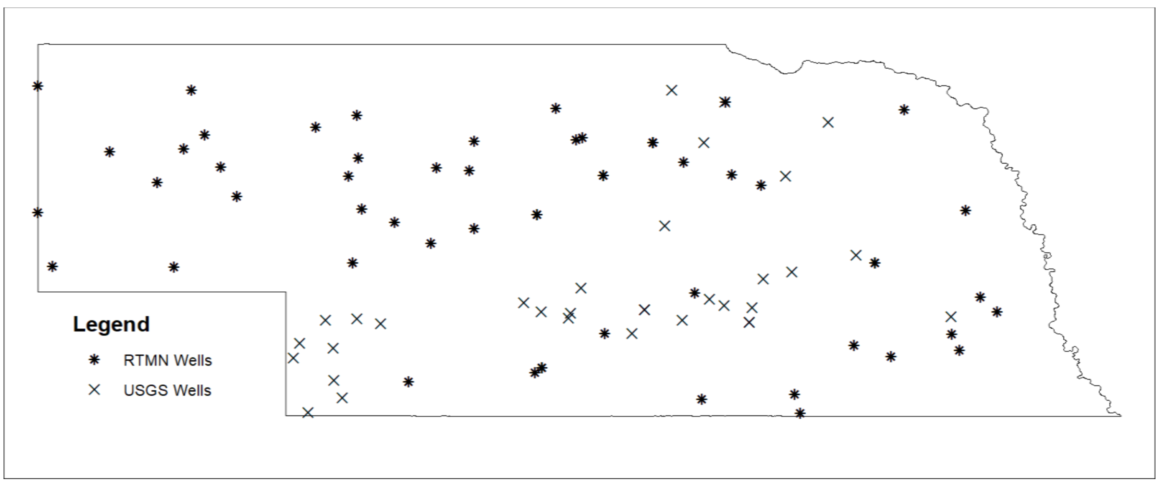

Figure 1 - Locations of USGS (X) and RTMN (*) wells in Nebraska

The University of Nebraska – Lincoln Institute of Agriculture and Natural Resources (IANR) has developed a project that provides real-time groundwater level monitoring across the state of Nebraska (UNL IANR 2017). The RTMN project uses remote telemetry, smart sensors, and wireless communication to collect and analyze hydraulic information from 56 locations around Nebraska (Figure 1). These groundwater levels have generally recent and wide ranging first readings from as early as 2002 to as late as 2015, but on average they start around 2007. This dataset also has significant gaps in daily readings, which further limits the value of the data. Despite these limitations, the data was used in order to gain wide ranging spatial distribution of observed groundwater levels across Nebraska. The daily well data from both datasets were averaged to weekly values to match the weekly GRACE data. Weeks with no data (usually caused by maintenance on the well infrastructure) were omitted from the final datasets.

2.1.3 The United States Drought Monitor

The U.S. Drought Monitor (USDM) was created in 1999 by the U.S. Department of Agriculture (USDA), the National Oceanic and Atmospheric Administration (NOAA) and the National Drought Mitigation Center (NDMC) (Svoboda et al. 2002) as a way to centralize and improve drought monitoring in the United States. The end product is a weekly map of drought severity (categorized as D0-D4) that incorporates objective weather and hydrologic data with local, state, regional, and federal input. The categories (Table 1) correspond to percentiles based on historical data and estimate the frequency of different drought severities at a given location and time of year.

USDM authors selectively incorporate many objective measurements and observational data such as weather variables (precipitation, temperature, and dewpoint), hydrologic levels (streamflow, snowpack, and reservoir levels), and vegetation indices (NDVI and other satellite-based greenness products). However, groundwater and soil moisture are not heavily represented, mostly due to a lack of observations and limited data access. GRACE percentile products have been accessible for Drought Monitor authors for several years (likely since 2013), and each author may have chosen to incorporate drought as shown by GRACE GWS or RZSM into the Drought Monitor. However, the accuracy and usefulness of these products had not been fully explored. Model-based approaches to these hydrologic variables, such as the GRACE groundwater and soil moisture percentiles evaluated in this research, may assist the Drought Monitor authors in creating a consistent and accurate representation of drought in the United States with known biases and patterns. Weekly USDM data were acquired in vector format (NDMC, USDA, NOAA, 2017) and converted to rasters corresponding to GRACE’s spatial resolution.

In addition to looking at how GRACE GWS and measured well levels compare, these well levels were compared to the USDM. This analysis translated the previously calculated well level percentiles into drought categories (Table 1). This was done to determine if these specific well levels show any significant relationship with the gold standard of drought monitoring. While USDM maps do have boundaries indicating “Short-term” (S) and “Long-term” (L) drought impacts, these impact and drought types were not considered in the comparisons. While the timeframe of the drought certainly effects impacts, including groundwater and soil moisture analyzed in this research, the processing to separate impacts in the quantitative comparisons limited this analysis. Additionally, the spatial designation of the time-scales of drought levels is not entirely consistent throughout USDM history, with some areas having clearly defined boundaries, and some areas just with the “S” or “L” placed without any boundaries.

2.1.4 Standardized Precipitation Index

The Standardized Precipitation Index (SPI) is the cumulative probability of a specific rainfall event occurring (McKee et al. 1993). Historical rainfall data is fitted to a gamma function to obtain a normal distribution. Time scales are determined by accumulation periods in months, with shorter time scales showing SPI frequently moving above and below zero and longer time scales showing fewer fluctuations. Monthly gridded SPI of 14 different accumulation periods (1 month – 12-month, 18-month, 24-month) were collected through the NDMC Drought Atlas (HPRCC and NDMC 2017) at 25 x 25 km spatial resolution. This data was previously processed by interpolating station SPI into the gridded format. While SPI is a measure of only one drought variable, precipitation, the seasonal meteorological patterns have a large effect on groundwater but are often only seen much later in time or on larger accumulation ranges. Fiorillo et al (2010) found SPI is best correlated with river discharge at 9- to 12-month accumulation periods. Accumulation periods of 12-month or longer also are highly tied to reservoir and groundwater levels (World Meteorological Organization, 2012). Soil moisture, on the other hand, would respond quicker to precipitation events. Accumulation periods between

1-month and 6-months are associated with soil moisture conditions (World Meteorological Organization, 2012).

2.1.5 The North American Land Data Assimilation System (NLDAS) Soil Moisture Data

The North American Land Data Assimilation System (NLDAS) is a quality controlled, spatially and temporally consistent land surface model (LSM). The project is a collaboration among NOAA/National Centers for Environmental Prediction's (NCEP) Environmental Modeling Center (EMC), NASA's Goddard Space Flight Center (GSFC), Princeton University, the University of Washington, NOAA/National Weather Service (NWS) Office of Hydrological Development (OHD), and NOAA/NCEP Climate Prediction Center (CPC). Modeled soil moisture percentiles were obtained using two NLDAS land surface models, Noah (Chen et al. 1996), and Variable Infiltration Capacity (VIC) (Liang et al. 1994) as well as the ensemble mean of Noah, VIC, Sacramento (SAC) (Burnash et al. 1973) and Mosaic (Koster and Suarez 1992). Each LSM simulates the processes of evapotranspiration, drainage, and vegetation uptake and depth slightly differently, and the output of each model can differ from each other. These LSMs are used in this research to compare to GRACE soil moisture percentiles as each LSM also produces soil moisture percentiles as outputs. GWS was not compared as groundwater is a fundamentally different quantity and NLDAS groundwater was not available for all models. NLDAS soil moisture data was gathered from NDMC projects at ~20 x 20 km resolution and produced at weekly intervals. This evaluation uses NLDAS data from April 2002 to December 2012.

2.1.6 2016 Northern Plains Flash Drought

In spring and summer 2016, a flash drought event developed rapidly over the Northern Plains, centered on western South Dakota, eastern Wyoming, southeastern Montana and northwestern Nebraska (USDM 2016). Flash drought refers to rapid onset drought events characterized by extreme atmospheric anomalies that persist for several weeks. Quickly deteriorating vegetation health, warm surface temperatures, increased evapotranspiration, and depleted soil moisture are typical conditions seen in flash drought events (Otkin et al. 2013). This region experienced impacts including forest and grassland fires, low forage production, decreased water quantity, and plant stress/death contributing to large economic losses for stakeholders. Through a National Integrated Drought Information Systems (NIDIS) funded project to study agricultural impacts of flash droughts and the drought monitoring capabilities of the Evaporative Stress Index (ESI) and USDM, a survey was sent to agricultural producers in the drought affected region (IRB#20160816292 EX). This survey was developed with expert input and pretested by agricultural extension personnel. It included questions focused on the timing and severity of individual impacts that allows researchers to track the onset and spread of drought.

The survey (Appendix I) was sent to 2389 agricultural producers living in 42 South Dakota, 16 Wyoming, 13 Nebraska, and 13 Montana counties that had experienced at least abnormally dry (D0) conditions by July 2016 according to USDM. A stratified random sample was taken that oversampled counties experiencing the most severe drought levels and undersampled the large number of counties that only experienced abnormal dryness. This sample was done in order to ensure that a sufficient number of responses were returned from areas experiencing each level of drought severity. The sampling frame was a list of producers participating in federal farms programs and was obtained from a Freedom of Information Request to the USDA Farm Services Agency.

The National Drought Mitigation Center (NDMC) administered the survey, with surveys mailed to the producers using the U.S. Postal Service. Following Dillman et al. (2009), a pre-survey letter was mailed to each producer in early November 2016, followed by the initial survey mailing in late November 2016 with a follow up survey mailing in January 2017. Out of the 2389 surveys mailed out, 516 (22%) were completed and returned to NDMC, 348 (15%) being completed by agricultural producers. Any survey not filled out by landowners actively engaged in agricultural production were excluded from the analysis.

In order to visualize a better spatial resolution of responses, the respondent's zip code was used to represent the location of each report. Counties represented too large an area to assume homogeneity of impacts, while pinpointed locations were not displayed because many addresses consisted of PO boxes and to respect the respondent's information privacy. It should be noted that individual responses could potentially integrate information from surrounding areas if land was owned in more than one zip code. Agricultural producer responses from 136 zip codes are represented in Figure 2.

Date reports were averaged by zip code to denote the first occurrence of impacts.

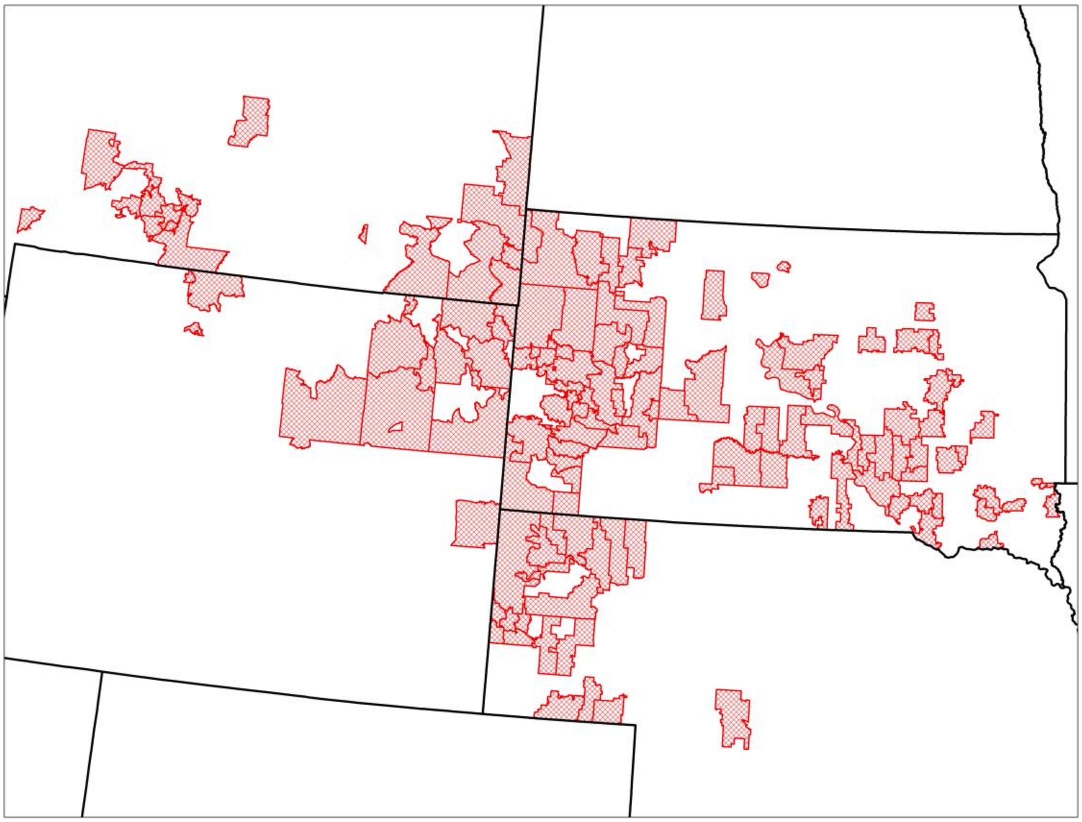

Figure 2 – Locations of individual zip codes from which completed surveys were received.

2.2 Comparison Methods

This research employs three main methods of comparing data. The first compared the gridded GRACE data to measured well point data. For April 2002 to December 2016, well levels were calculated as a percentile rank of the total historic record for that well. Each well location was sampled from the GRACE GWS time series using two spatial sampling techniques, nearest and cubic, and compared to well levels and well percentiles. Nearest sampling takes only the value of the pixel that each location is in, whereas cubic calculates a weighted average value based on the 16 nearest pixels (ESRI 2017).

The two time-series were then compared using Spearman's Rank Correlation

$$r_s = \rho_{rgX}, \rho_{rgY} = \frac{cov(rg_X, rg_Y)}{\sigma_{rgX}, \sigma_{rgY}} \quad \text{Eq. 1}$$

where ρ denotes the correlation coefficient for ranked variables, $cov(rg_X, rg_Y)$ is the covariance of the ranked variables, and σ_{rgX} and σ_{rgY} are the standard deviations of the ranked variables. Spearman rank correlation was selected as it describes the association strength between any of the two datasets (GRACE-wells, GRACE-USDM, GRACE-SPI, and GRACE-NLDAS), while its calculation assumptions also fit the data. Additionally, Spearman correlations are robust to outliers (Croux and Dehon 2009). Pearson correlation requires data to be normally distributed, linear and equally distributed about the regression line. Over the specific time periods of GRACE, normal distribution cannot be assumed and linearity would need to be proven. Spearman's assumptions however, are the data must be ordinal and its result measures how monotonic the relationship is. Because this data is ranked and converted to percentile, the ordinal assumption is fulfilled. The correlation of well and GRACE data was done using an R script and base R correlation function (Appendix II).

If a relationship between GRACE data and the well data exists, the correlation is expected to be negative. This is due to well levels being reported as distance from the surface – the smaller the number, the closer the water table is to the surface and more water is in the ground. Conversely, larger amounts of groundwater in GRACE are indicated by larger numbers.

The second method spatially compared two gridded time-series datasets. To assess the strength and spatial extent of the relationship between GRACE products and other DIs and indices, a python script was created to calculate Spearman's Rank correlation coefficient pixel by pixel (Appendix III), so that each time-series comparison created a single map with each cell value representing the magnitude of correlation (-1 to +1). This script's method converted each raster into a numPy array and correlated each array index, then converted it back into a raster using built-in ArcPy functions. The method can only be used when both datasets are exactly the same cell size and grid extent, so each dataset had to be resampled and clipped to match each other. The code was validated by sampling several points of the time-series data and manually calculating the correlation making sure it matched with the output map at those points.

The final method of comparison consisted of qualitative and quantitative comparisons of GRACE with the survey data from the 2016 Northern Plains flash drought as a case study. The qualitative analysis was simply a visual comparison of the onset and extent of drought using month-by-month USDM and GRACE GWS and RZSM maps. The quantitative analysis looked at the evolution of USDM drought levels and GRACE percentiles as compared to the date of first occurrence of certain drought conditions as reported by stakeholders in the region by averaging USDM and GRACE GWS and RZSM values over all zip codes during a 12-week period centered on the date that each impact first occurred for each individual zip code. Re-centering the time series for each zip code allows for a more consistent comparison of the datasets because it accounts for the different timing of drought impacts across the region. All grid points located within each zip code were identified using a shape file and then used to compute the mean for each dataset and zip code. An average time series was then computed for each dataset and survey question using the re-centered time series from each respondent. The resultant time series provide an opportunity to evaluate the consistency between the timing of the reported impacts and the characteristics of the drought monitoring datasets.

2.3 Statistical Methods

At the $\alpha < 0.05$ confidence level, each individual correlation coefficient can be assessed as being significantly different than zero using the student's t test with n-2 degrees of freedom in Eq (2a) and solved for r_{crit} in Eq (2b)

$$t = r\sqrt{\frac{n-2}{1-r^2}} \qquad \text{Eq. 2a}$$

$$r_{crit} = \frac{t}{\sqrt{(t^2+n-2)}} \qquad \text{Eq. 2b}$$

where r_{crit} is the significant correlation value, t is the critical t-value, and n is the sample size. When comparing well data with GRACE data, certain weeks will have less than the maximum number of observations (well maintenance or quality assurance removal), thus making the observation sample size for significance calculations highly variable. This problem does not exist when comparing raster data as each cell has data throughout the time-series. Table 2 gives the observation sample size of each spatial comparison along with the critical r to determine if the value is significantly different than zero at $\alpha < 0.05$. After each individual well or cell correlation was calculated, the values were averaged to determine the general trends – the same significance values still apply to the average values. The standard deviation of the correlations was also measured as a way to describe the variability of the comparisons.

Table 2 – Critical correlations at $\alpha < 0.05$ for spatial correlations

Spatial Comparison	**Sample Size (n)**	$\mathbf{r_{crit}}$
GRACE - USDM	770	0.071
GRACE - SPI	129	0.171
GRACE - NLDAS	560	0.083

CHAPTER 3 – RESULTS

3.1 Groundwater Well Comparison

The point comparisons using both USGS and RTMN well datasets with different spatial averaging techniques yielded enormous variance. Over all 33 locations, USGS well levels show a highly variable, but generally negative correlation with GRACE GWS (Fig 3a). The 56 RTMN locations indicate a very similar pattern of variability but overall negative correlation (Fig 3b). Both datasets suffer from large ranges in the correlation. While the majority of wells had a negative correlation to GRACE, which was expected if both datasets represent the same quantity, a significant amount was spread into near zero and high positive correlations. Overall, USGS wells had slightly stronger average correlations with nearest correlation values USGS = -0.274, and RTMN = -0.243. The cubic average correlation values were nearly identical at USGS = -0.273 and RTMN = -0.245.

A

B

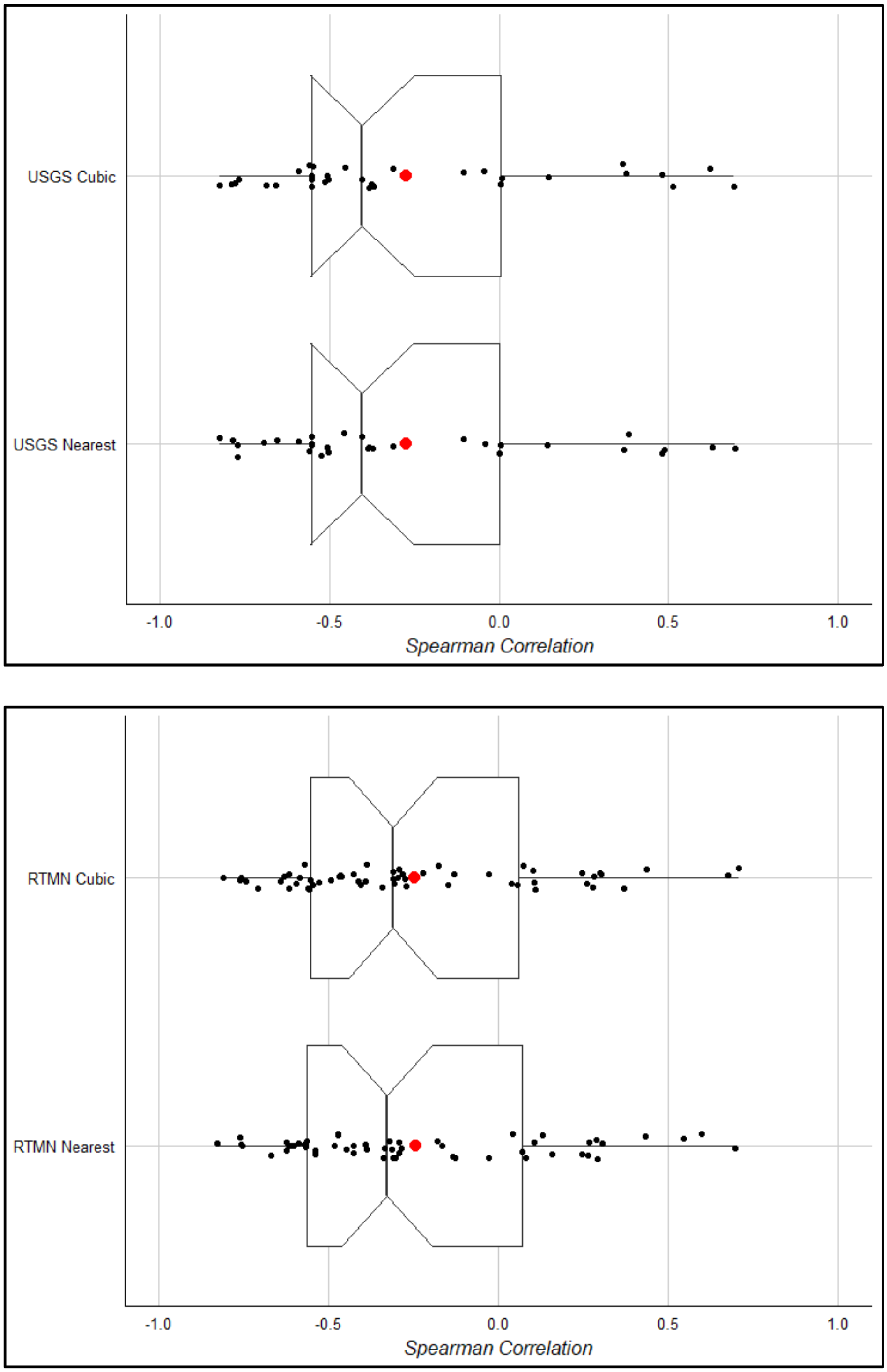

Figure 3 - USGS (a) and RTMN (b) correlation values between wells and GRACE percentiles. The red dot represents the mean, the middle notch represents the median, and the box represents the 25th and 75th percentiles.

Figure 4 illustrates the correlation relationships between the well percentiles converted to drought levels and USDM drought levels at each well location. In this case, a strong relationship of similar trends would be positive due to the processing of the well percentiles taking the inverse to convert to drought levels. Overall USGS wells showed weak positive correlation with the USDM but had high variance. RTMN wells, on average, had weak negative correlation and a larger variance, with the average value very close to zero. This result is further discussed in Chapter 4.

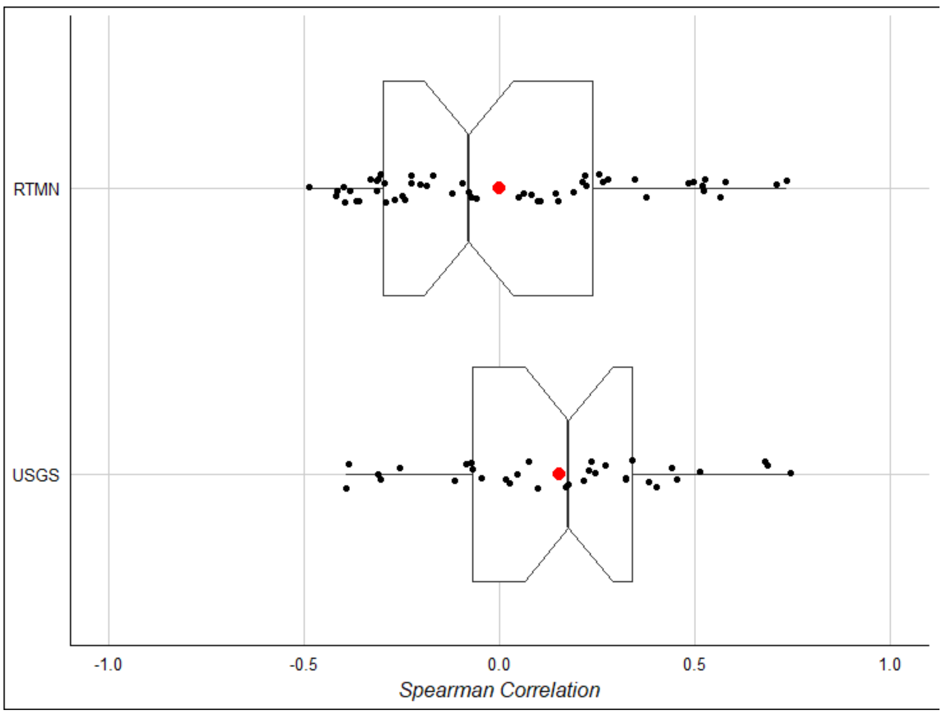

Figure 4 - USGS and RTMN well percentiles converted to drought levels correlated with USDM drought levels. The red dot represents the mean, the middle notch represents the median, and the box represents the 25^{th} and 75^{th} percentiles.

As the two well datasets have a general spatial distribution over the state, Figure 5 illustrates the spatial pattern of correlation values. The result shows the same significant variability as the individual comparisons. In general, the eastern part of the state shows slightly better (more negative due to GRACE percentiles and well levels trending in opposite directions when indicating the same changes) correlations, while the western, specifically southwestern portion shows worse (more positive) correlations with the occasional strong negative outlier.

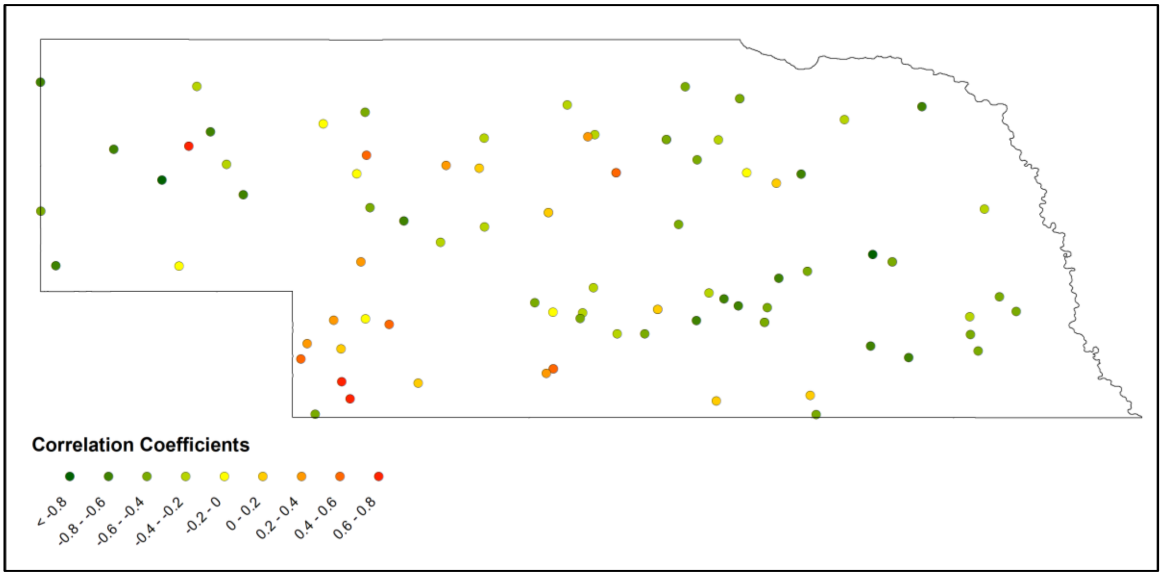

Figure 5 – Spatial distribution of GRACE GWS and USGS and RTMN well level correlation coefficients using the nearest sampling technique. Positive correlations indicate poor agreement, negative indicate good agreement due to the numbers trending in opposite directions when showing the same change.

3.2 Spatial Correlations

The gridded comparison of GRACE and other drought indicators (SPI, NLDAS soil moisture, and USDM) provides complete coverage over CONUS. The analysis of this relationship should give an indication if these products provide any skill at monitoring and assessing drought from an objective point of view. All correlations are represented with a decimal between -1 and 1. -1, represented by dark red, is a perfect, negative correlation, 1, represented by dark green, is a perfect, positive correlation, and 0, represented by yellow, means the data is not monotonically related and has no correlation.

3.2.1 GRACE - USDM

Both GWS and RZSM dataset comparisons provide five maps - one complete time series (Fig 6a and 6b) and four seasons broken into the commonly used meteorological seasons, December-January-February (DJF), March-April-May (MAM), June-July-August (JJA), and September-October-November (SON) (Figures 7a and 7b). The USDM drought levels were compared including both short and long-term droughts as shown on the published USDM maps. This was because the separation of the gridded data into short and long-term droughts was not feasible in this study's timeframe. This separation is further discussed in the conclusions and future work section.

The complete timeseries GWS – USDM comparison had an average correlation of 0.434 indicating a significant positive relationship (Table 2). However, the spatial distribution varied widely from near-zero correlation to many areas with above 0.75 correlation (Fig 6a). The South and Southeast, Midwest, California and Northern Rocky Mountains show very strong positive correlation. Parts of New England as well as much of the High Plains, Pacific Northwest, and Colorado/New Mexico yield lower and more sporadic agreement. There is a notable and sharp gradient from good correlations in East Texas and Oklahoma to low positive or near-zero correlations in West Texas and New Mexico. Other similar gradients are on the Idaho – Washington/Oregon border and in Central Arizona. These gradients do not seem to strictly follow topographical features. The differences in correlations may be explained by the number of drought events captured in the 2002-2016 timeframe, where areas experiencing more droughts have more variation to be correlated with GRACE data.

Table 3 – Complete and seasonal correlation average values and standard deviations between GRACE levels and USDM levels

CORRELATION	**MEAN**	**STD**
GWS COMPLETE TIME-SERIES	0.434	0.165
GWS DJF	0.395	0.216
GWS MAM	0.385	0.208
GWS JJA	0.487	0.186
GWS SON	0.462	0.220
RZSM COMPLETE TIME-SERIES	0.383	0.130
RZSM DJF	0.351	0.182
RZSM MAM	0.377	0.171
RZSM JJA	0.389	0.157
RZSM SON	0.351	0.186

As for the seasonal comparisons, the cool seasons of DJF and MAM showed a lower average, but very similar spatial patterns. Note there are large areas of NODATA, indicated by areas of white, as certain areas of GRACE data converted to drought levels had a covariance of zero, i.e. never dropped below 30%. The warm seasons of JJA and SON showed large correlation increases nearly everywhere. SON's higher values seem to emit from the high correlations becoming stronger, while the low correlations becoming lower. This SON comparison yields the first regions of the U.S. with overall near zero or slightly negative correlations in Colorado and New Mexico.

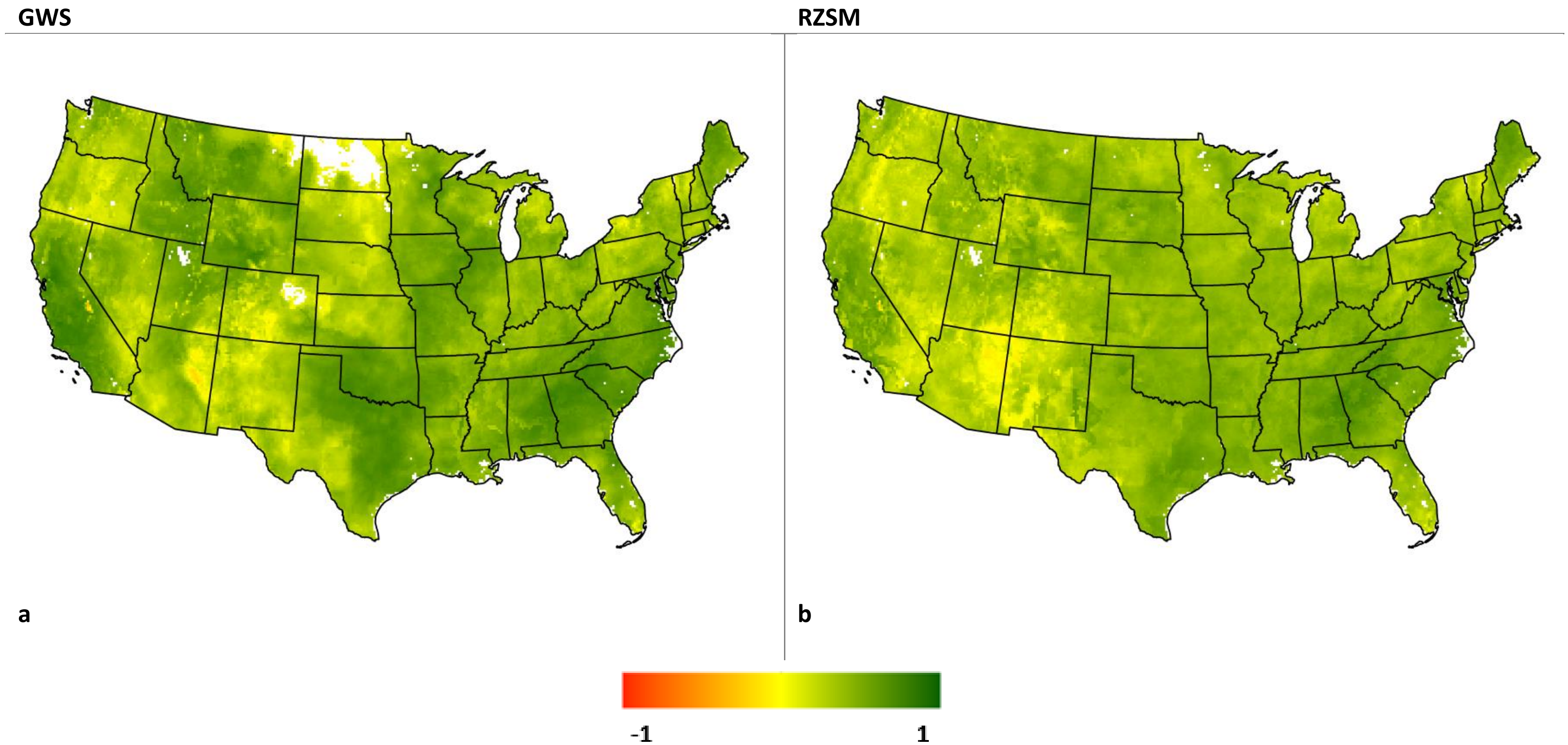

Figure 6 - Correlations between GRACE drought levels and USDM drought levels. GWS (a), RZSM (b)

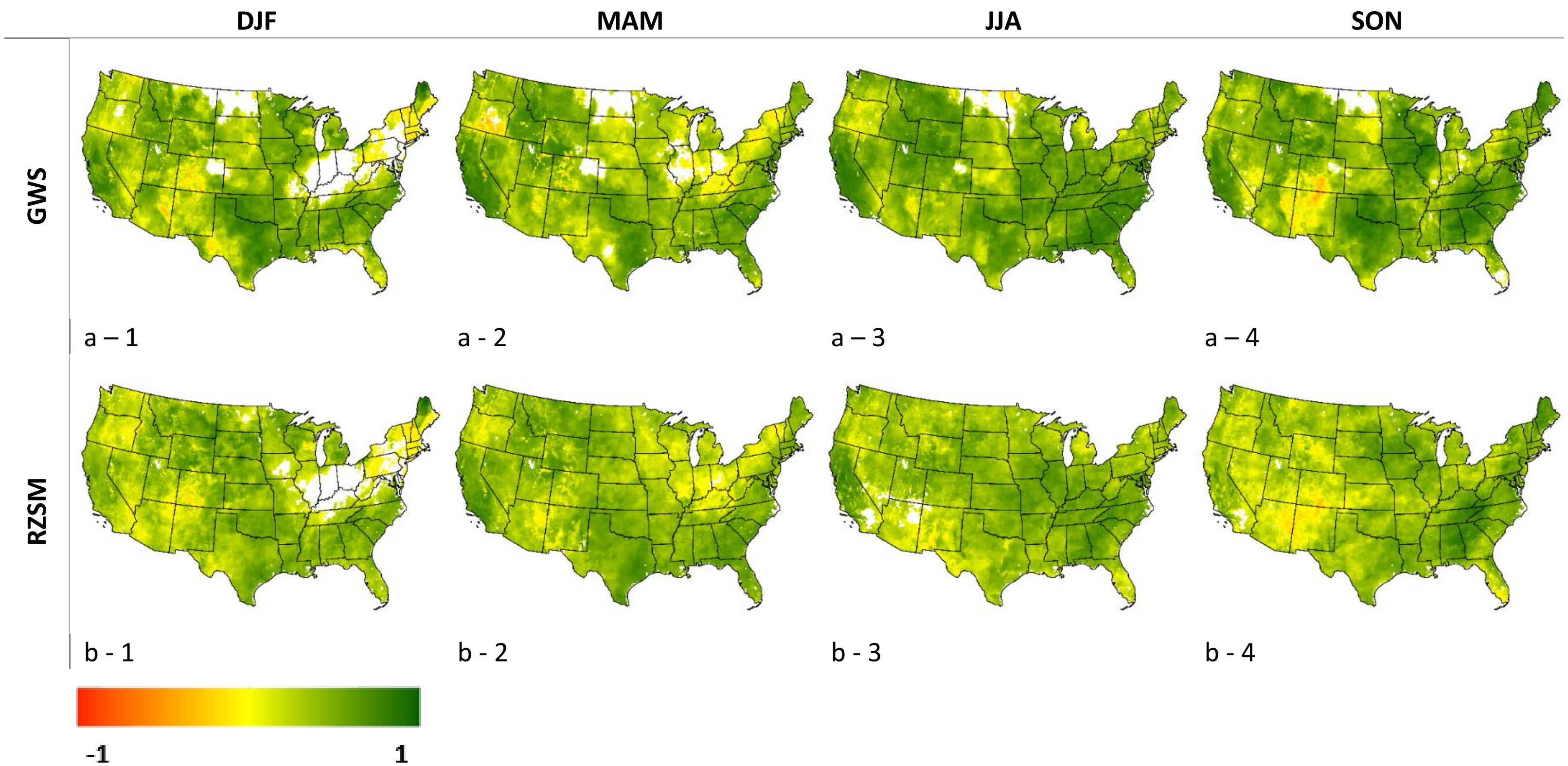

Figure 7 – Seasonal correlations between GRACE drought levels and USDM drought levels. GWS (a), RZSM (b)

The RZSM – USDM complete time-series comparison has an average correlation of 0.383, as well as a more consistent (lower variance) distribution across the U.S. Visually, the lower correlation than the GWS comparison is clear, but the homogeneity also becomes more apparent. The spatial pattern is overall very similar to the GWS comparison. The most distinctive changes are the loss of sharp gradients in Texas, Arizona, and Idaho, as well as a significant increase in average correlation over South Dakota, Nebraska, and Kansas.

As with GWS comparisons, the RZSM seasonal calculations show similar spatial patterns to the complete time-series. In this case DJF and SON have the lowest average correlations, whereas JJA and MAM show the best agreement. The difference between seasonal averages, however, is not as strong as the GWS seasons. The most distinct change in the seasons is the much greater correlations around the Midwest in JJA and SON seasons, and the low correlations of California in DJF and SON seasons. The differences revealed by comparing the complete time-series to seasonal correlations clearly indicate there are times and places where agreement is higher and lower between GRACE drought products and the USDM.

In the attempt to remove any covariance between GRACE and USDM (as authors may have incorporated GRACE data post 2013), a correlation analysis was performed for data up to December 2012. Figure 8 presents the difference between correlation maps for this period (Full period – 2012 period). Overall, the average GWS correlation for the 2002-2012 period very slightly increases from 0.434 to 0.447, while the average RZSM correlation slightly increases from 0.383 to 0.401. The largest areas of difference are in California and much of the western and southwestern U.S. California, Nevada, northwestern New Mexico, and some of northern Texas, and see better correlations when post 2012 data is included. However, much of Arizona, the Idaho-Washington-Oregon border, and western Texas have better correlations when post 2012 data is not included. The RZSM differences are in the same pattern, but less extreme.

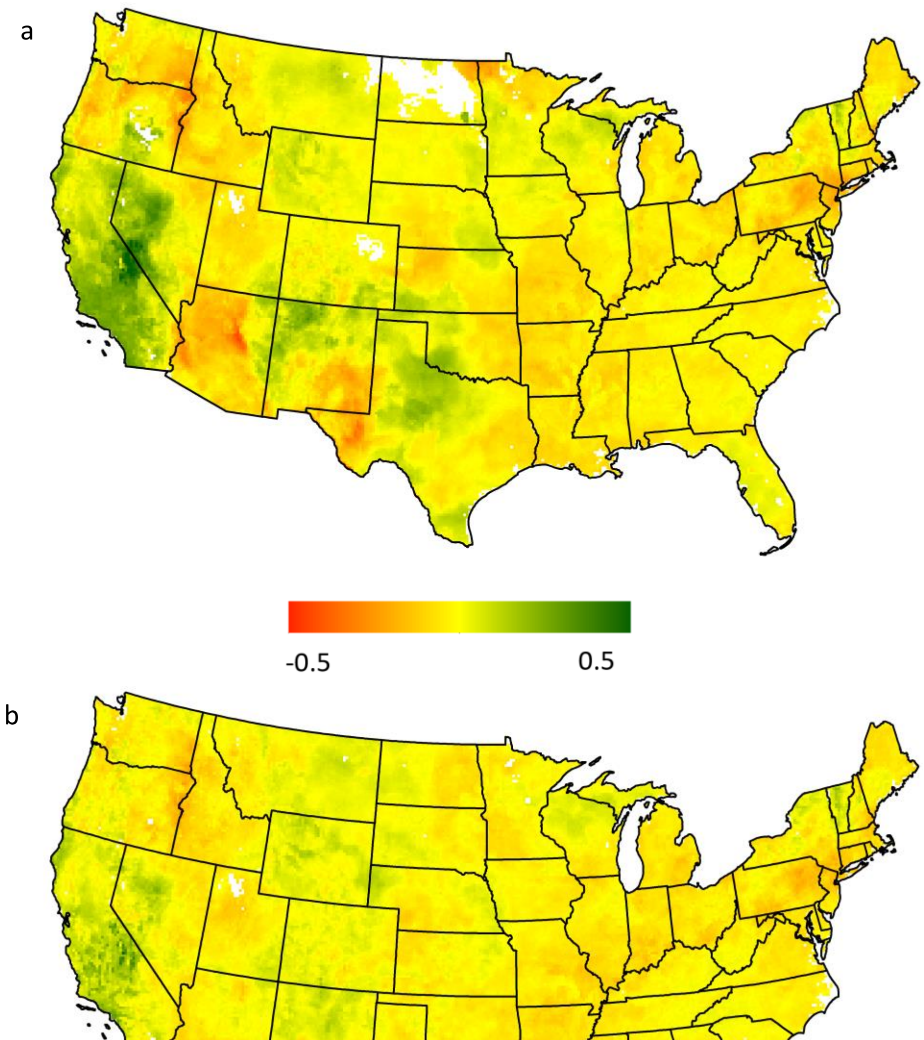

Figure 8 – Difference between full period correlations (2002-2016) and truncated period correlations (2002-2012) for GWS (a) and RZSM (b). Green indicates the full period correlation are higher, while red indicates the 2002-2012 period correlations are higher.

3.2.2 GRACE – SPI

Correlations between SPI and GRACE GWS and RZSM percentiles provide a valuable comparison of two objective drought indices. While SPI is computed as standard deviations of precipitation anomalies, the relative changes positive or negative are compared. Table 4 shows the average results of the 14 SPI accumulation periods that are compared to GRACE GWS and RZSM. Figures 9 and 10 show the spatial patterns of each accumulation period correlation with GWS and RZSM respectively.

All comparisons yielded similar spatial patterns. Starting with 1-month accumulation period, SPI - GWS correlations were generally poor across the U.S. with a pocket of reasonably good correlations in Missouri and the Kentucky-Tennessee-North Carolina-Virginia area. This accumulation period also has the most homogeneity as demonstrated by the low standard deviation. As the accumulation period becomes longer, correlations increase. Throughout the accumulation periods, the spatial pattern is consistent and the largest change occurs in the jump from 12-month to 18-month. Overall the eastern, south, and far west regions of the U.S. show consistently high correlations, peaking at the 11- and 12-month accumulation periods. This result agrees with the previously mentioned research regarding the best groundwater and streamflow correlations to SPI at 9-month or later accumulation periods. The central plains of South Dakota, Nebraska, and Kansas, along with large areas of mountainous terrain in Montana, Wyoming, and Colorado typically show the lowest correlations, but are still generally positive. These same areas also see large increases in correlations with the inclusion of 18- and 24-month accumulation periods. The amount of spatial variability, that is variation from one pixel to another in the same accumulation period correlation, is generally consistent throughout the accumulation periods as shown in the standard deviations in Table 4.

The RZSM comparisons establish that small temporal accumulation periods have higher correlation than their GWS comparison counterparts, with 1-month periods yielding 0.44 correlation. Increasing the accumulation period still increases the correlation to a maximum average value of 0.585 at 3-months and stays very constant up until 12-months. Accumulation periods of 18- and 24- month shows highly decreased correlations. The spatial pattern is nearly identical to the GWS comparisons, with slightly more homogeneity across the country, corresponding to the generally lower standard deviations. Additionally, the highest average value for RZSM comparisons was slightly higher than for GWS.

Table 4 – Correlation average values and standard deviations between GRACE GWS and RZSM percentiles and SPI anomalies for different accumulation periods.

Accumulation Period	**GWS**		**RZSM**	
	Mean	**Std**	**Mean**	**Std**
1 Month	0.131	0.099	0.440	0.116
2 Month	0.284	0.148	0.571	0.133
3 Month	0.363	0.164	0.585	0.127
4 Month	0.417	0.170	0.581	0.121
5 Month	0.456	0.170	0.574	0.119
6 Month	0.485	0.168	0.568	0.119
7 Month	0.506	0.168	0.561	0.120
8 Month	0.522	0.166	0.557	0.121
9 Month	0.533	0.165	0.550	0.124
10 Month	0.539	0.166	0.538	0.130
11 Month	0.542	0.167	0.525	0.131
12 Month	0.543	0.167	0.512	0.132
18 Month	0.511	0.182	0.427	0.152
24 Month	0.488	0.191	0.395	0.158

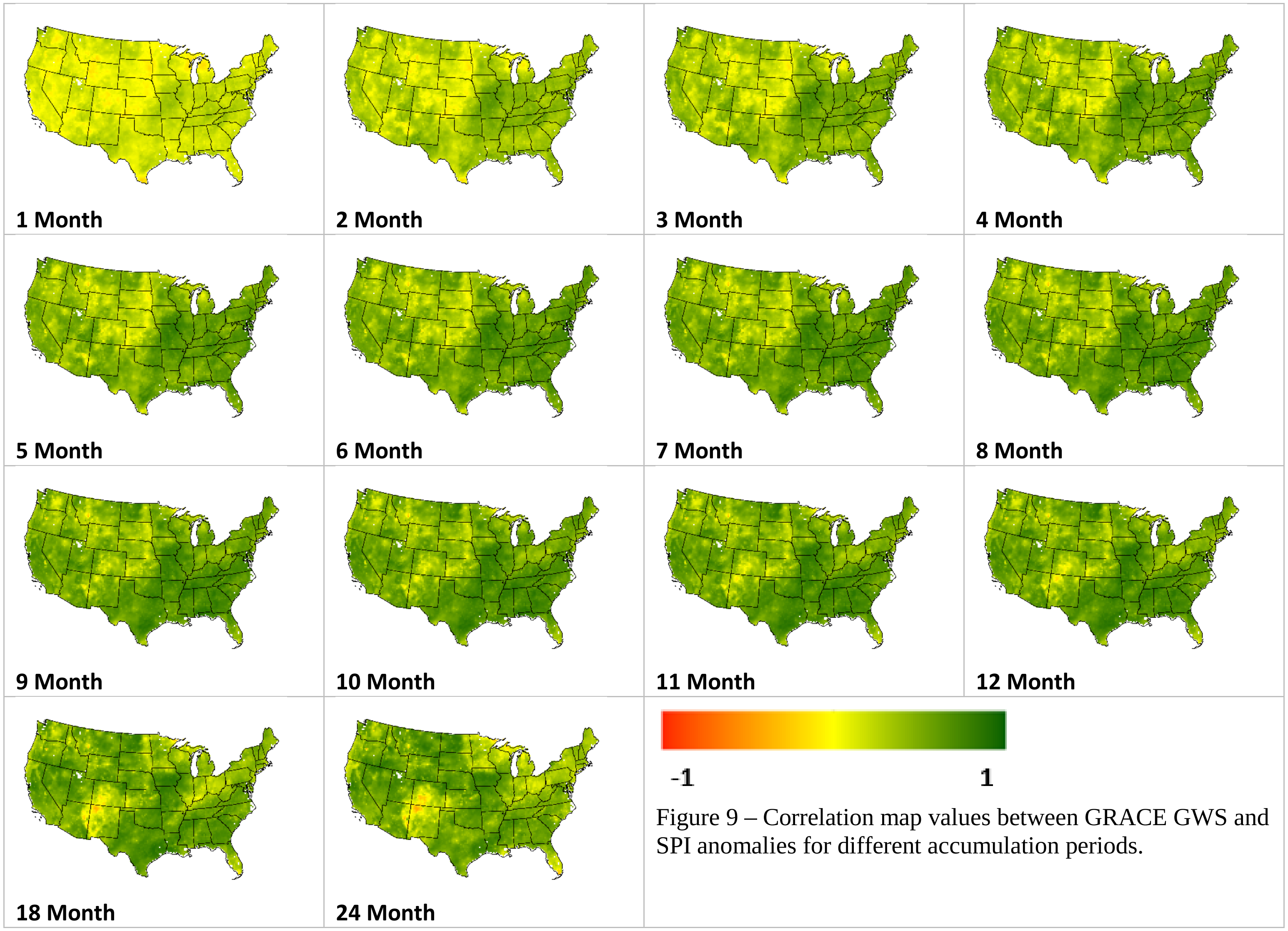

Figure 9 – Correlation map values between GRACE GWS and SPI anomalies for different accumulation periods.

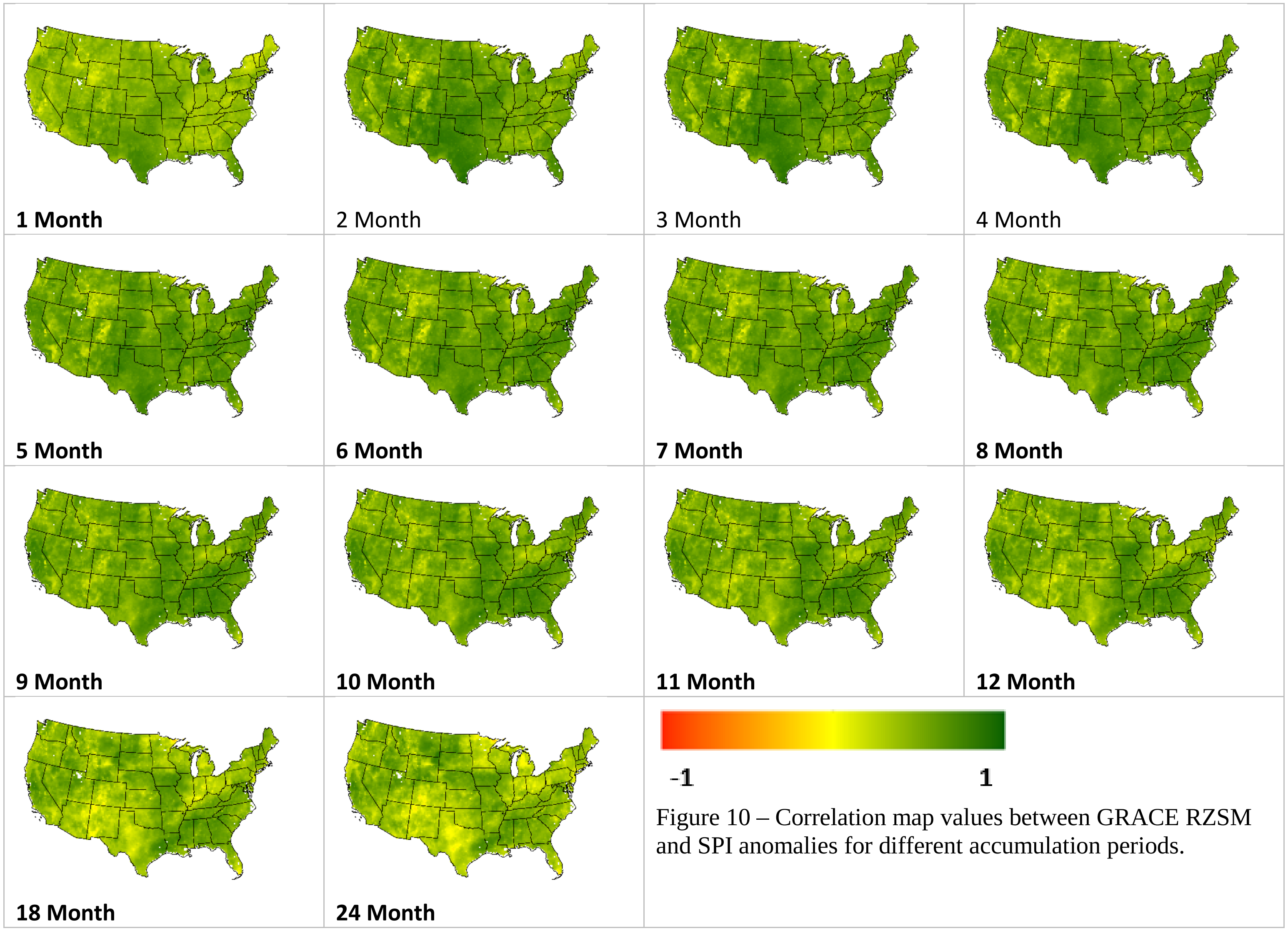

Figure 10 – Correlation map values between GRACE RZSM and SPI anomalies for different accumulation periods.

GWS seasonal comparisons of 9-, 10-, 11-, and 12-month accumulation periods, chosen due to their highest average correlation, showed the transition seasons of MAM and SON generally had the lowest correlations with similar patterns to the complete time-series maps (Fig 11). All SPI seasonal values are given in Table 5. The best average correlations appear in the summer months of JJA and winter months of DJF. MAM shows far lower correlations across the High Plains at 9- and 10-month accumulation periods and SON sees a similar lower correlation pattern for the High Plains at all four accumulation periods. Throughout all seasons and accumulation periods, the Southern U.S. has consistently high, positive correlations.

Seasonal RZSM comparisons of 2-, 3-, 4-, and 5-month accumulation periods, again chosen due to their highest average correlations, show generally higher correlations during MAM, JJA, and SON, and significantly lower correlations during the winter months of DJF (Fig 12). The variance of the correlations is also much higher in DJF than in the other three seasons. The winter months also show severe deterioration of correlations in high peaks of the Rocky Mountains of Colorado and Wyoming across all four accumulation periods. JJA shows significant improvement of correlation in the same region for all accumulation periods, while MAM and SON are similar to the complete-time series values.

Table 5 – Correlation average values and standard deviations between GRACE GWS and RZSM percentiles and SPI anomalies for different seasons and accumulation periods.

GWS	**Mean**	**Std**	**RZSM**	**Mean**	**Std**
DJF - 9 Month	0.561	0.222	DJF - 2 Month	0.539	0.223
DJF - 10 Month	0.583	0.210	DJF - 3 Month	0.575	0.221
DJF - 11 Month	0.584	0.207	DJF - 4 Month	0.572	0.208
DJF - 12 Month	0.575	0.208	DJF - 5 Month	0.568	0.211
MAM - 9 Month	0.519	0.211	MAM - 2 Month	0.583	0.188
MAM - 10 Month	0.538	0.208	MAM - 3 Month	0.601	0.184
MAM - 11 Month	0.565	0.197	MAM - 4 Month	0.626	0.166
MAM - 12 Month	0.584	0.192	MAM - 5 Month	0.617	0.160
JJA - 9 Month	0.567	0.178	JJA - 2 Month	0.654	0.161
JJA - 10 Month	0.572	0.175	JJA - 3 Month	0.653	0.150
JJA - 11 Month	0.575	0.183	JJA - 4 Month	0.632	0.151
JJA - 12 Month	0.570	0.195	JJA - 5 Month	0.621	0.155
SON - 9 Month	0.543	0.213	SON - 2 Month	0.625	0.166
SON - 10 Month	0.537	0.210	SON - 3 Month	0.618	0.169
SON - 11 Month	0.533	0.213	SON - 4 Month	0.603	0.169
SON - 12 Month	0.537	0.213	SON - 5 Month	0.588	0.165

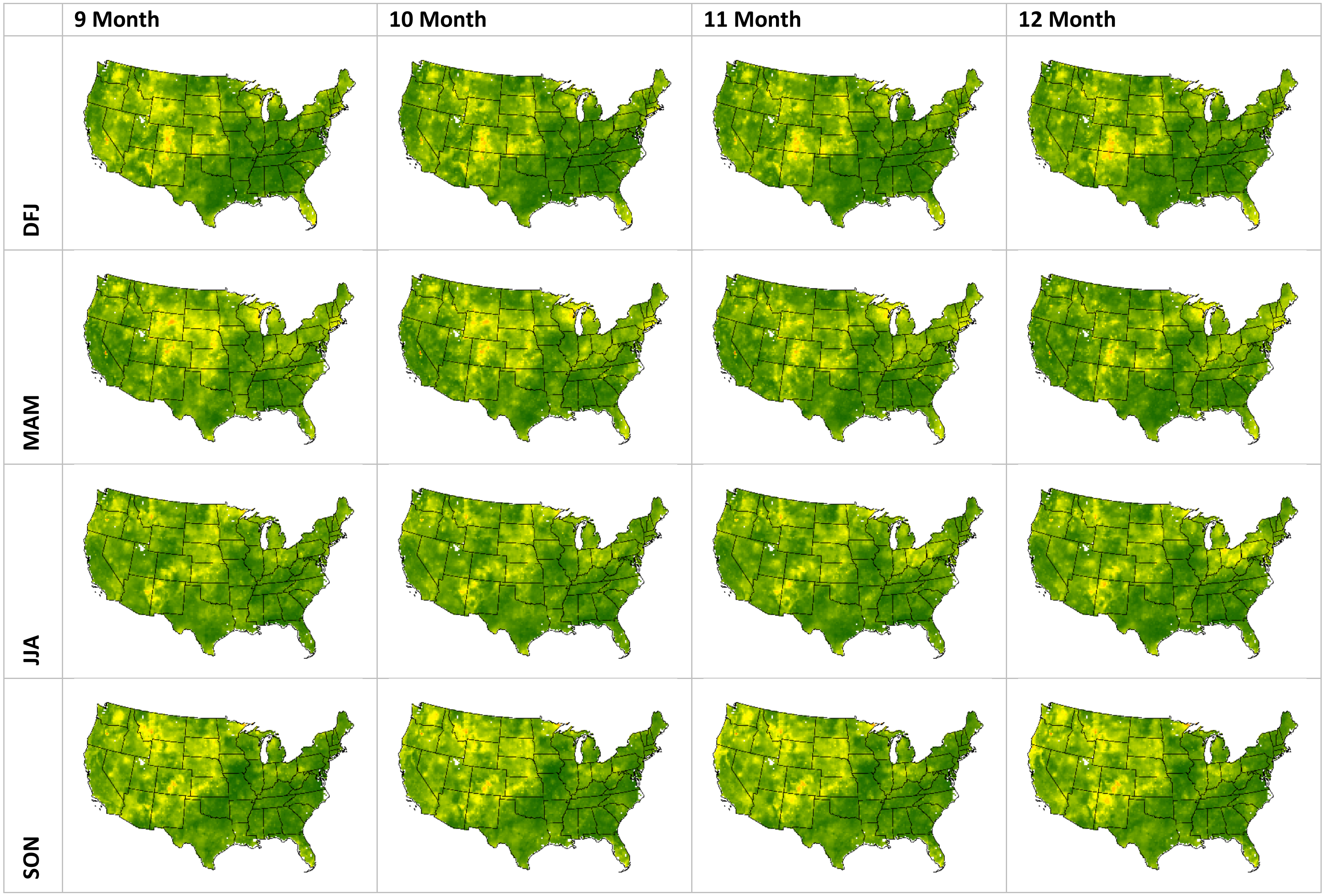

Figure 11 – Correlation values between GRACE GWS percentiles and SPI anomalies for different seasons and accumulation periods.

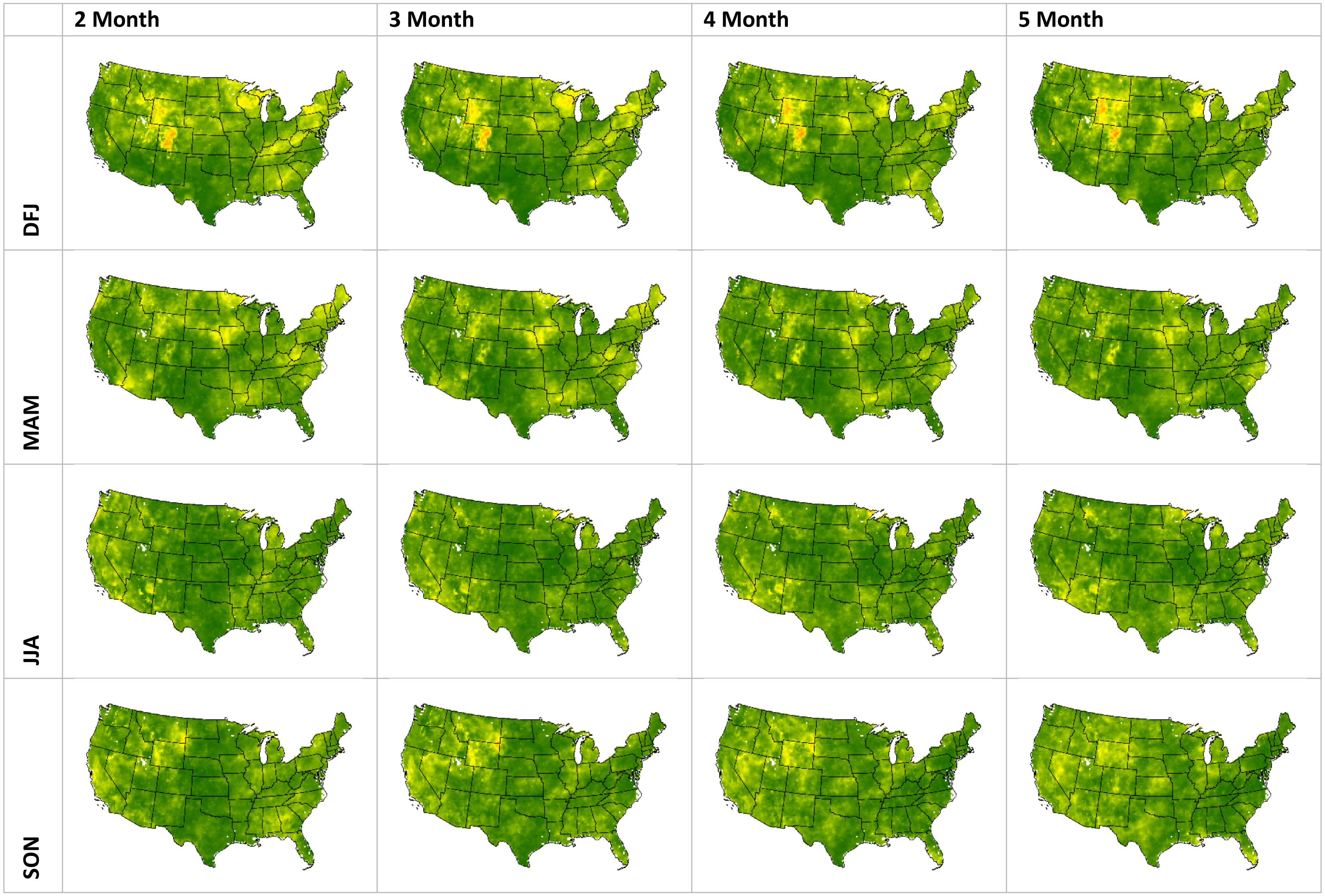

Figure 12 – Correlation values between GRACE RZSM percentiles and SPI anomalies for different seasons and accumulation periods.

3.2.3 GRACE – NLDAS

The model to model comparisons of GRACE RZSM percentiles and NLDAS LSM RZSM percentiles cannot definitively tell where GRACE performs well and where it does not. Because both datasets are models, fed often times by identical meteorological and energy flux observations (Xia et al. 2012a, Xia et al. 2012b), this comparison only yields the spatial patterns of where there is general agreement and disagreement. The GRACE data has the hope to produce more accurate, more useful information through the assimilation of GRACE satellite gravity data. NLDAS soil moisture can be used as a reference observed map of soil moisture data due to the lack of a national soil moisture network, and itself is can be used as a drought indicator by drought monitor authors.

The ensemble of Noah, VIC, SAC, and Mosaic models showed the strongest agreement with GRACE soil moisture, while Noah and VIC showed similarly strong, but slightly less agreement (Table 6). The ensemble model also yielded the lowest standard deviation, and again, Noah and VIC showed similar but higher standard deviations. The three complete time-series comparisons showed nearly identical spatial patterns, with strong agreement over the central Great Plains, medium agreement in the eastern U.S. and sporadically good and poor agreement over the mountainous central-western and western U.S. (Fig 13). The Rocky Mountains show a clear signal in these maps, with lower agreement near the high peaks. This mountain signal is also potentially seen in the Cascades and Sierra Nevada ranges of the Pacific Coast, as well as a weaker signal in the lower Appalachian Mountains of South Carolina and Georgia.

Table 6 – Correlation average values and standard deviations between GRACE RZSM percentiles and NLDAS Ensemble (ENS), Noah, and VIC soil moisture percentiles for different seasons

RZSM Comparison	Mean	Std
ENS Complete Time Series	**0.660**	**0.124**
ENS DJF	0.597	0.190
ENS MAM	0.639	0.154
ENS JJA	0.682	0.123
ENS SON	0.703	0.121
NOAH Complete Time Series	**0.605**	**0.135**
NOAH DJF	0.500	0.218
NOAH MAM	0.568	0.179
NOAH JJA	0.643	0.133
NOAH SON	0.654	0.135
VIC Complete Time Series	**0.602**	**0.131**
VIC DJF	0.533	0.199
VIC MAM	0.576	0.166
VIC JJA	0.639	0.135
VIC SON	0.649	0.150

Seasonally, it is clear, JJA and SON have significantly higher average correlations, along with generally lower standard deviations. Figure 14 corresponds to this result, with nearly all areas showing improved agreement between GRACE RZSM and NLDAS modeled SM. The largest increases appear in the Western U.S., but the area still has some sporadic distribution of good and poor correlations. While still boasting a strong, positive correlation, DJF consistently has the lowest agreement, followed with mild improvement by MAM. The strongest deterioration during DJF appears over Wyoming and Colorado, with a few areas indicating significant negative correlation. DJF and MAM also see some lowered agreement within the Kentucky-Tennessee area.

Overall, this model-model comparison of GRACE and NLDAS soil moisture yields the highest average correlations out of all the gridded datasets computed in this study. Even with the comparison of two models, significant differences are found by season and region.

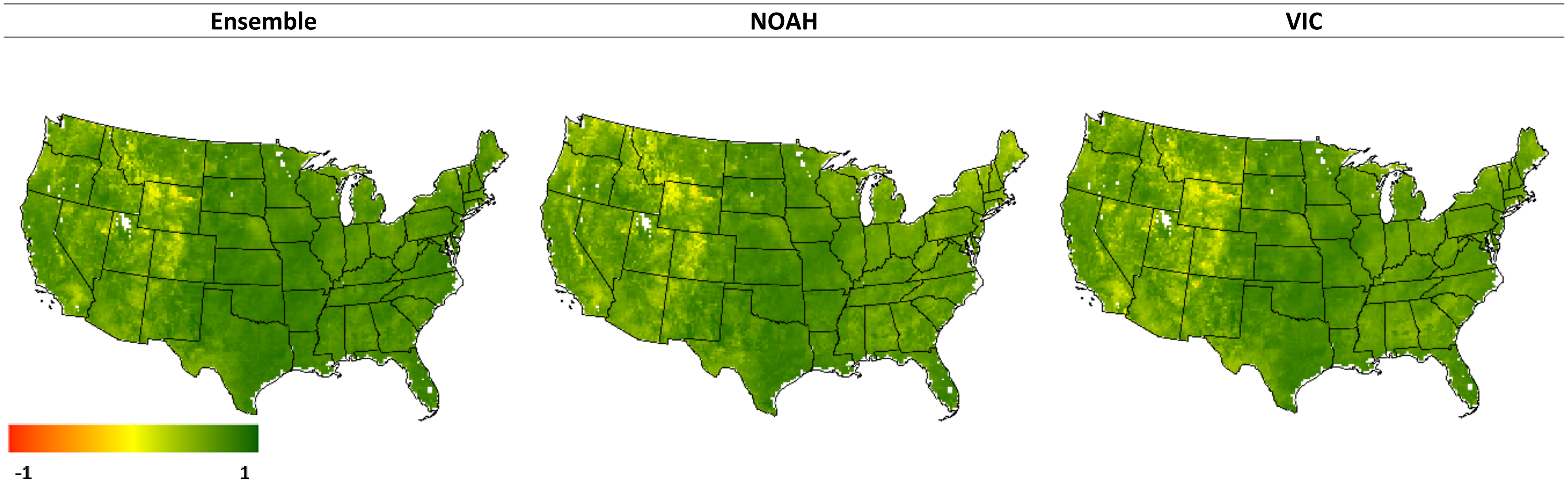

Figure 13 – Correlation values and between GRACE RZSM percentiles and NLDAS soil moisture percentiles

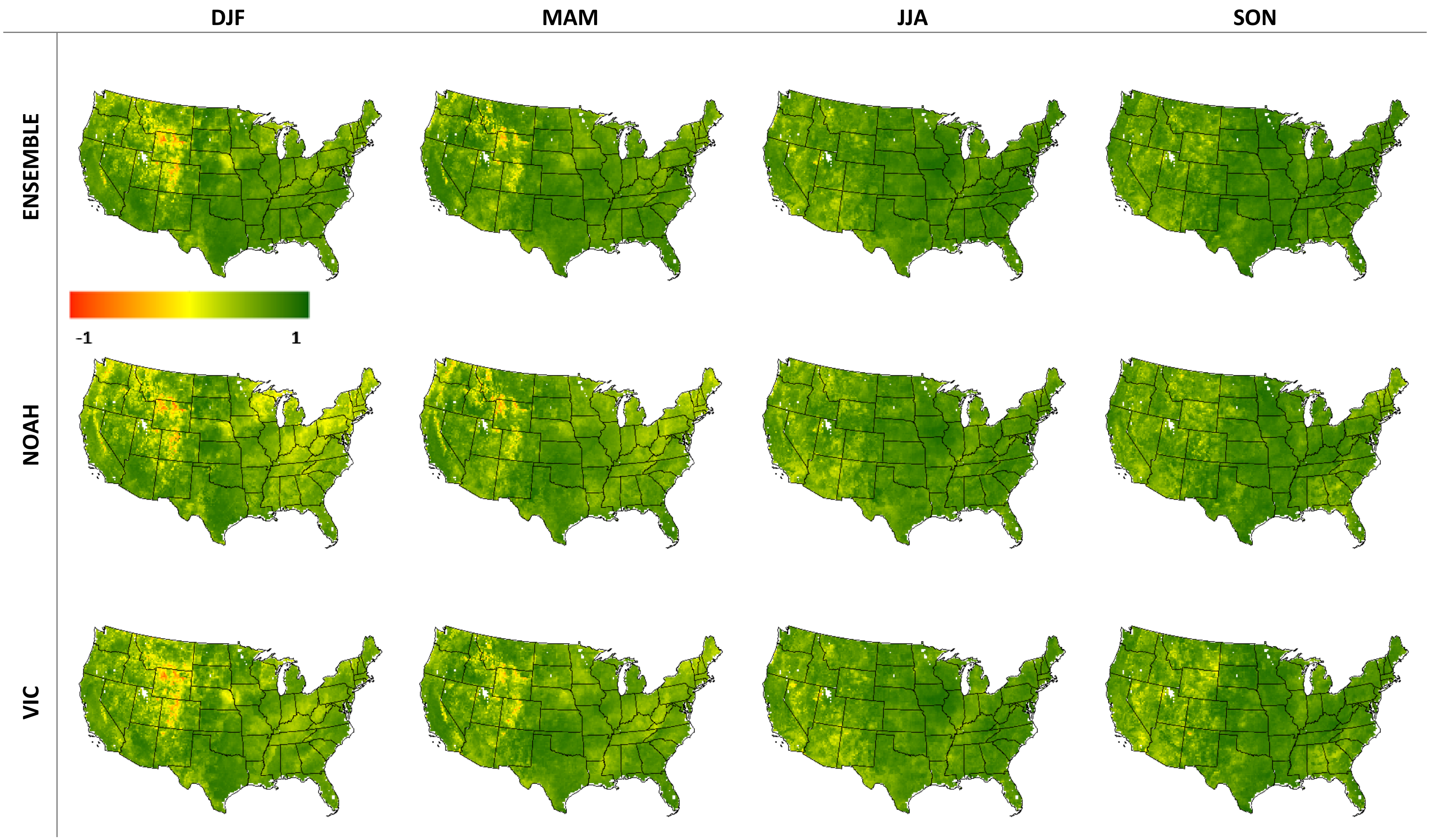

Figure 14 – Correlation values and between GRACE RZSM percentiles and NLDAS soil moisture percentiles for different seasons

3.3 2016 Northern Plains Flash Drought Analysis

The stakeholder survey (Appendix I) included sets of questions regarding producer decisions and ecosystem impacts of drought onset. This research focuses on the multi-part question, Q3, where respondents were asked to mark if certain drought impacts occurred, and if they did, when they first started. Table 7 gives the total results from the respondents, the number of responses for each condition, the percentage of responses that indicated the condition did or did not occur on their land and the average date of first occurrence of each condition from those responding it did occur.

Table 7 – Results of stakeholder survey regarding occurrence and start date of drought conditions

	DID IT OCCUR?			
	N/A	**NO**	**YES**	**MEAN DATE**
A. Decreased topsoil moisture (n=329)	2%	4%	94%	May 14
B. Decreased subsoil moisture (n=319)	3%	7%	90%	May 21
C. Delayed or lack of plant emergence (n=317)	9%	26%	65%	May 20
D. Delayed or lack of plant growth (n=321)	2%	11%	87%	May 31
E. Plant stress (crop or pasture) (N=318)	2%	6%	92%	Jun 16
F. Plant death (crop or pasture) (N=302)	9%	40%	51%	June 27
G. Poor grain fill (n=301)	46%	15%	39%	June 29
H. Deteriorating range conditions (n=319)	5%	8%	86%	June 17
I. Decreased forage productivity (n=316)	5%	9%	86%	June 13
J. Lowered water levels in ponds, streams, or other water sources (n=318)	11%	9%	80%	June 6
K. Lack of water in ponds, streams, or other water sources (n=317)	13%	16%	70%	June 16
L. Wells unable to keep up with livestock or irrigation needs (n=307)	28%	56%	16%	June 30
M. Fire (n=311)	23%	59%	17%	July 6
N. Infestations of insects or other pests (n=305)	18%	57%	25%	June 15

This survey indicates nearly all responding stakeholders observed drought conditions during 2016, with observations of decreased top and subsoil moisture, and plant stress showing the highest percentage (94%, 90%, and 92%, respectively). Many producers also saw decreased forage productivity (86%) and deteriorating range conditions (86%) as well as a large portion observing lowered water levels (80%) and even lack of water (70%). While fire and pests did occur for some producers, this event was predominately a quick onset meteorological/agricultural drought that was not prolonged enough for more severe, long-term impacts. These reports show a multi-faceted drought strongly and quickly impacting soil moisture, local water resources, and vegetation health.

A general timeline of events emerges based on the mean dates of first occurrence. It begins with decreased top and subsoil moisture and poor initial crop growth in mid to late May followed by more severe symptoms of plant stress, deteriorating range and forage conditions, and low water levels through mid-June, and finally in late June first reports of crop death, poor grain fill and insufficient water resources take place. The use of mean date in this fashion does ignore regional differences in the intensification of the drought, but in general this logical progression of events increases the confidence in the results of this survey.

This section will go month by month, March through August, looking at the USDM levels of drought with overlaid zip codes of reports of first occurrence of decreased topsoil moisture (QA), decreased subsoil moisture (QB) and lowered water levels in ponds, streams, or other water sources (QJ) and visually compare them with GRACE GWS and RZSM. Blue outlined areas in the Figures 15-20 represent zip codes that first saw the drought condition in that individual month, while black outlines represent zip codes that saw the first occurrence prior to that individual month. This approach also highlights differences between USDM and GRACE drought products, as well as differences between drought products and stakeholder perception.

3.3.1 Monthly Analysis

March

As the first major month of reports of decreased soil moisture, March also shows extensive areas of abnormally dry conditions (D0), with several areas of moderate (D1) and small areas of severe (D2) drought (Fig 15). This dryness is predominately in Montana, North Dakota and Wyoming, with some areas of South Dakota also affected. The dryness and drought conditions from the USDM correspond to warm monthly conditions coupled with dryness from the previous fall and winter. These warm conditions seem to agree with the beginning of reports of decreasing topsoil and subsoil moisture. There are also a few reports of lowered water levels, which may be in part due to the previous seasons' dryness, amplified by the month's warm temperature.

GRACE RZSM shows a wide range of soil moisture conditions, from very poor to very good. Many of the reports of decreased topsoil moisture occur within the area of high percentile GRACE soil moisture conditions. However, several of the reports of decreased top and subsoil moisture do occur in areas where GRACE RZSM is low. GRACE GWS shows the region generally has near normal water levels, with some below average levels mostly occurring in Wyoming. The new reports of lowered water levels also occur in Wyoming, but it is difficult to tell if the two reports (northeast and north-central Wyoming) are in agreement.

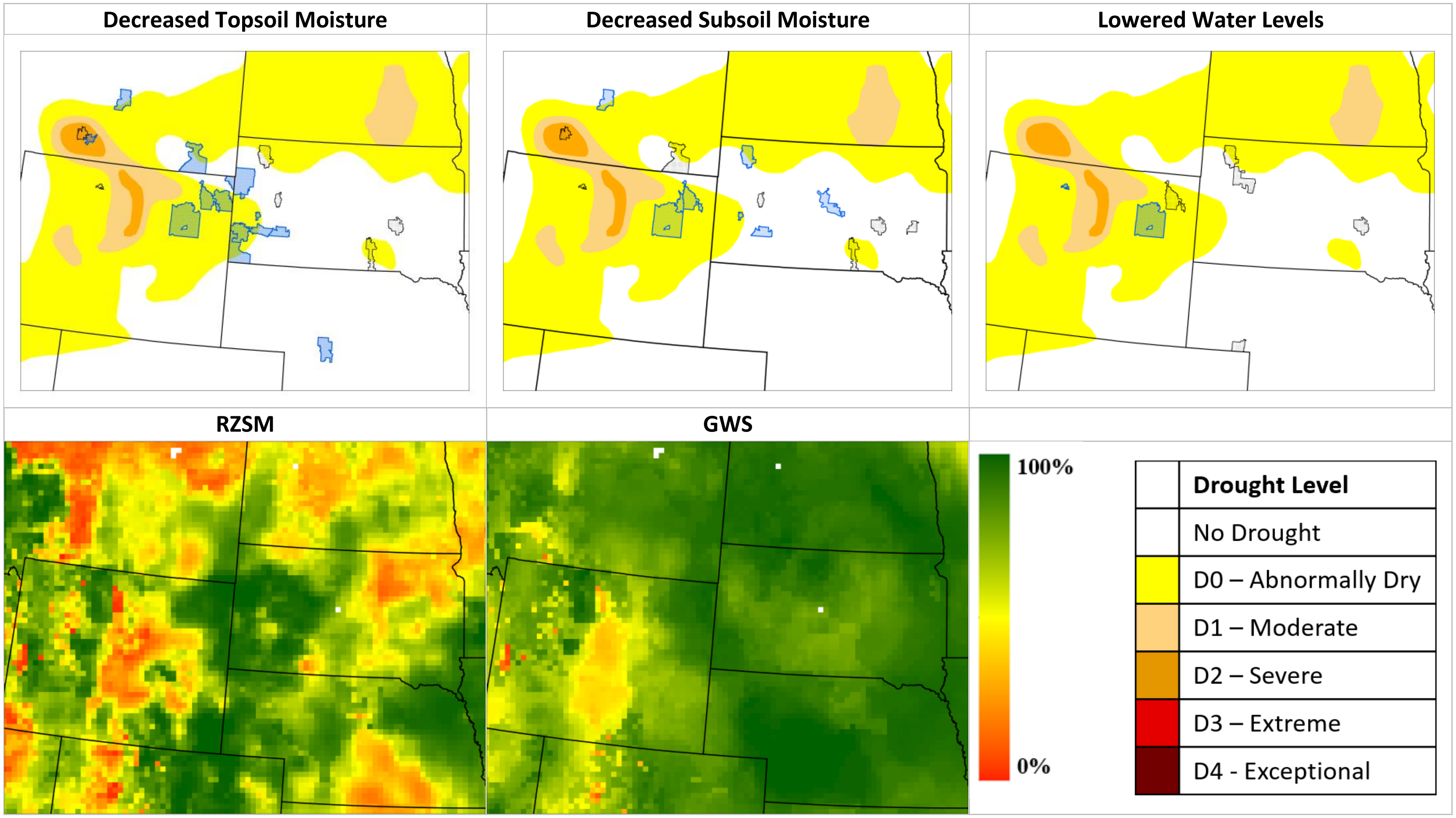

Figure 15 – Maps showing locations where survey respondents observed decreased topsoil moisture (a), subsoil moisture (b), and lowered water levels (c) with USDM map valid 31 March 2016 overlaid. Black (blue) hatched areas denote zip codes where conditions were observed prior to (during) March. Maps showing GRACE RZSM (d) and GWS (e) valid March 31 where green represents higher percentiles and red low percentiles.

April

The month of April sees a significant rise in the number of reports of all three conditions from the area. Most of the additional reports of decreased top and subsoil moisture (Fig 16) are on in western South Dakota, eastern Wyoming, and southeastern Montana. USDM shows significant improvement in dryness, with far fewer areas considered dry by the USDM and GRACE RZSM and GWS products. The majority of new reports of decreased soil moisture occur in areas not considered dry. GRACE RZSM is again, highly variable, but does see deteriorated conditions along the South Dakota-Wyoming border where many reports originated. Most of the rest of the remaining region showed good or improved soil moisture conditions.

The reports of lowered water levels were in slightly better agreement with areas the USDM considered abnormally dry or in drought. GRACE GWS showed only slightly lower conditions than March, with a large portion of Wyoming with lowered water levels. Any GWS trend was difficult to analyze visually due to the slow change.

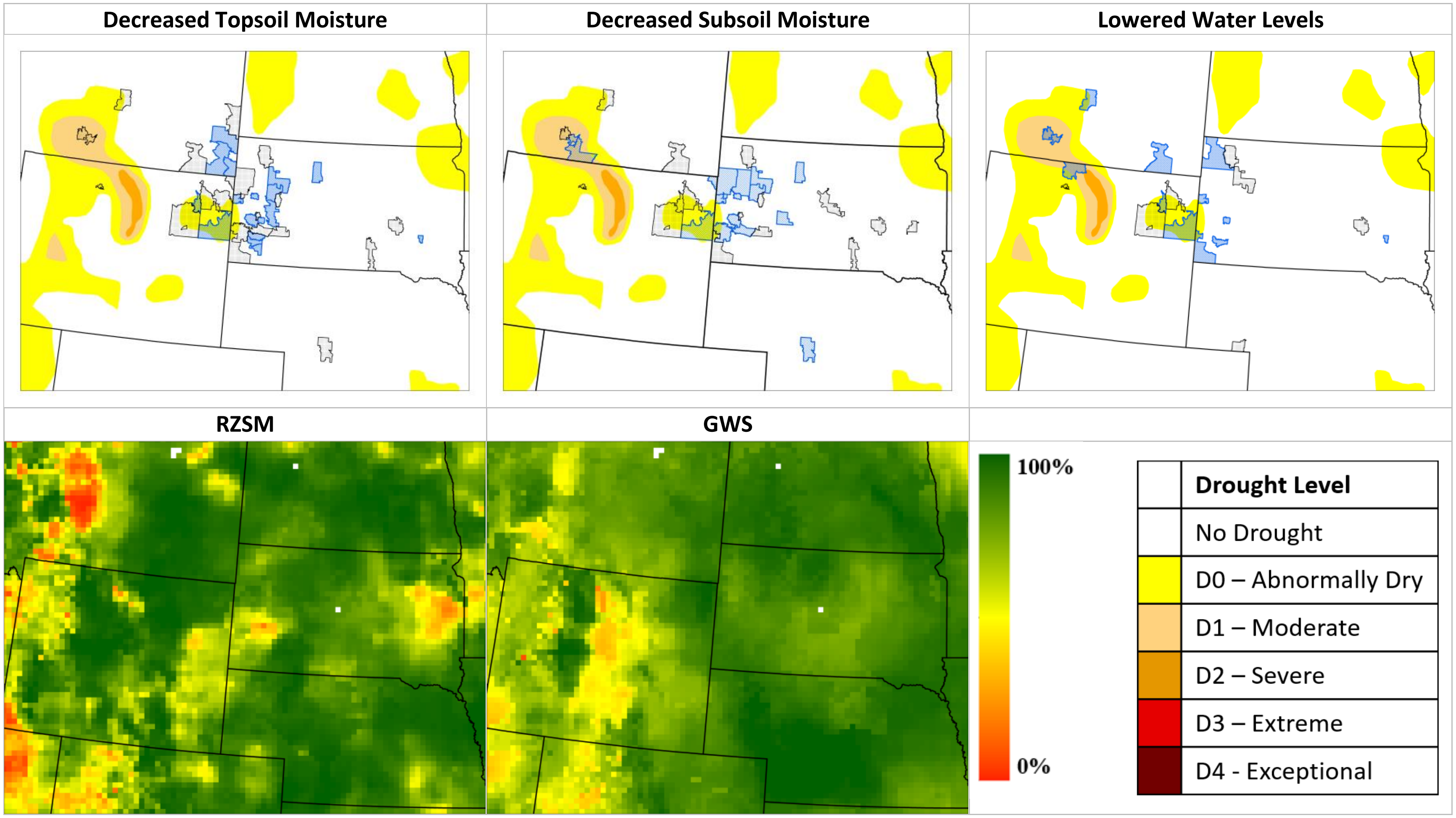

Figure 16 – Same as figure 14 but all images valid 30 April 2016.

May

By May 31, dryness and moderate drought emerged in the South Dakota – Wyoming border region. There was slight improvement in the drought conditions of central and western Wyoming. Reports showed a widening area of decreased topsoil and subsoil moisture around the South Dakota-Wyoming border and into central South Dakota. Decreasing topsoil moisture reports (Fig 17) primarily occur on the edges or slightly away from areas the USDM considered in dryness or drought, whereas decreased subsoil moisture seems to be concentrated more closely with the regions depicted as dry by USDM. Several more reports of lowered water levels also appear, similar to decreased subsoil moisture, close to the USDM drought region.

GRACE RZSM appears to capture the same trend as the stakeholder observations, showing significant deterioration across South Dakota. RZSM spatially agrees very well with both reports of decreased topsoil and subsoil moisture, as well as showing similar trends to USDM. GRACE GWS shows slightly lowered conditions across the region, but changing very slowly, and does not have significant areas below 30-40%. While the lowering of water levels could agree with GWS, the drought conditions seem decoupled from GRACE GWS at this time. This is likely due to the slow nature of groundwater change and the more substantial effect of long-term droughts on groundwater compared to short-term drought groundwater effects.

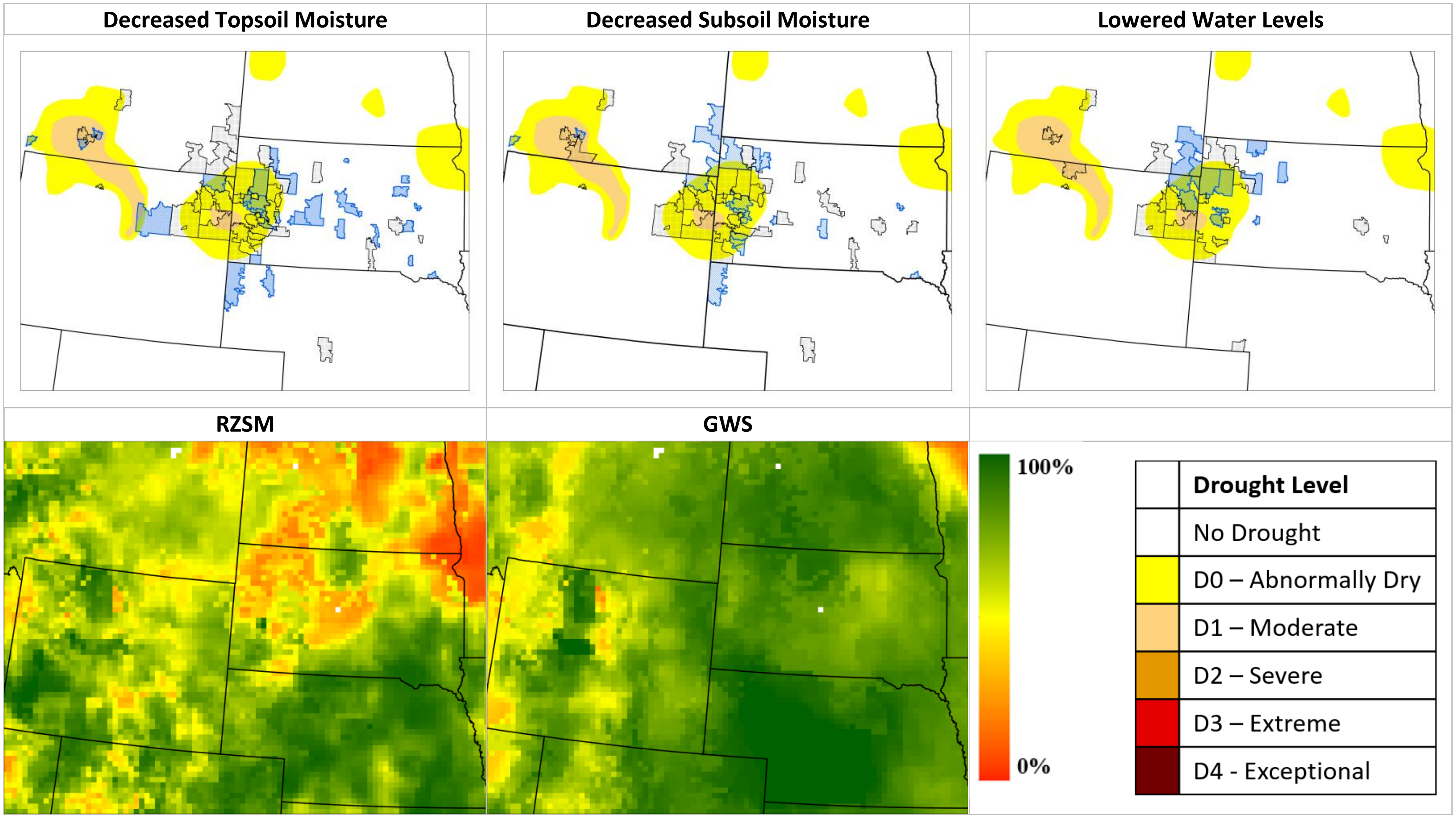

Figure 17 – Same as Figure 14 but all images valid 31 May 2016

June

A very rapid intensification of drought took place by the end of June. The USDM showed the first indications of extreme drought (D3), centered in the South Dakota – Wyoming border region. Widespread dryness (D0) and moderate (D1) to severe (D2) drought was also present across all of western South Dakota, northern and northeastern Wyoming, southern and southeastern Montana, and southwestern North Dakota. Many more reports of decreased topsoil and subsoil moisture also appear (Fig 18). Decreased topsoil moisture reports (QA) are scattered and widespread, with many appearing on the fringes of USDM dry regions, but some also corresponding to the intensification event in D1 or D2 regions. Decreased subsoil moisture reports (QB) are slightly more centralized and mostly located within or on the border of dry regions. There are also a substantial number of additional reports of lowered water levels (QJ) that clearly agree with the USDM categorization, appearing in D0, D1, D2, and D3 drought areas.

There is a clear signal of deteriorating conditions in GRACE RZSM with the entire area in very low percentiles. Many regions, including most of South Dakota, the Nebraska panhandle, and eastern Wyoming are in single digit percentiles. RZSM shows very high agreement with the scattered reports of QA and QB, with all zip codes reporting those conditions having very low percentiles. GRACE GWS does show deterioration, but not to the extent of USDM or RZSM, lowering only several percent mainly over South Dakota, Wyoming, and Montana. Fewer areas are above 50% groundwater and much of South Dakota and Wyoming show distinct declines since May. The reports of lowered water levels, for the most part, are where GWS had the largest decreases. One area in particular, east-central South Dakota, had GWS lower than the rest of the region, with some percentiles in the 20 to 30% range. This area was on the fringes of USDM dryness classification, but stakeholders reported water levels lowering.

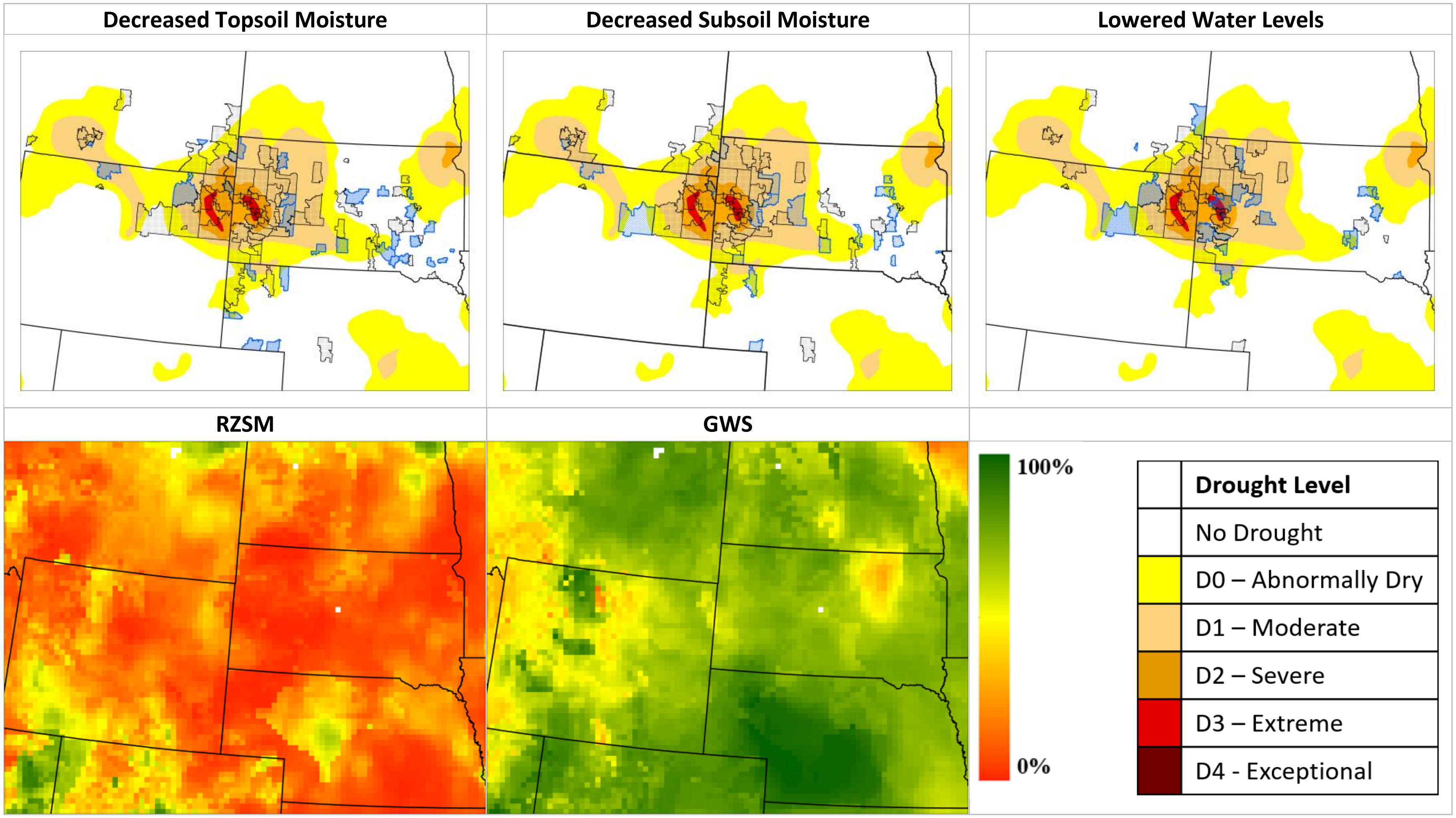

Figure 18 – Same as Figure 14 but all images valid 30 June 2016

July

By the end of July, the drought had reached its peak intensity and distribution from a USDM perspective. The drought region of the South Dakota – Wyoming border, along with a small area of southeastern Montana were in D3 drought, with widespread areas of D2, D1, and D0 across South Dakota, Wyoming, southern Montana, and northwestern Nebraska. Most new reports of decreased topsoil moisture (QA) (Fig 19) occurred in south-central South Dakota and northwestern Nebraska. These specific regions had a fairly rapid onset of dryness between June and July. Reports of decreased subsoil moisture (QB) follow a similar pattern to topsoil moisture reports, and both QA and QB fall very much within USDM regions of at least D0 dryness. Areas reporting lowered water levels occur mostly scattered across South Dakota. Again, these reports overlap or border with the USDM drought regions.

While the GRACE RZSM showed overall improving soil moisture conditions compared to June, the core drought region was still at very low percentiles, spreading far into Wyoming and the Nebraska panhandle. There was very good agreement with the single digit percentiles, in red, and both reports of decreased top and subsoil moisture, as well as with USDM maps. The main areas that showed improvement between June and July in RZSM were areas of central-western Nebraska and parts of North Dakota. Continuing the slow, downward trend, GRACE GWS sees a similar, but delayed pattern. There was still deterioration with some areas below the 30% level, but in general GWS levels did not respond to these quick drying events. Across South Dakota, there was slight deterioration, but not severe, and the spatial occurrence did not match well with lowered water level reports.

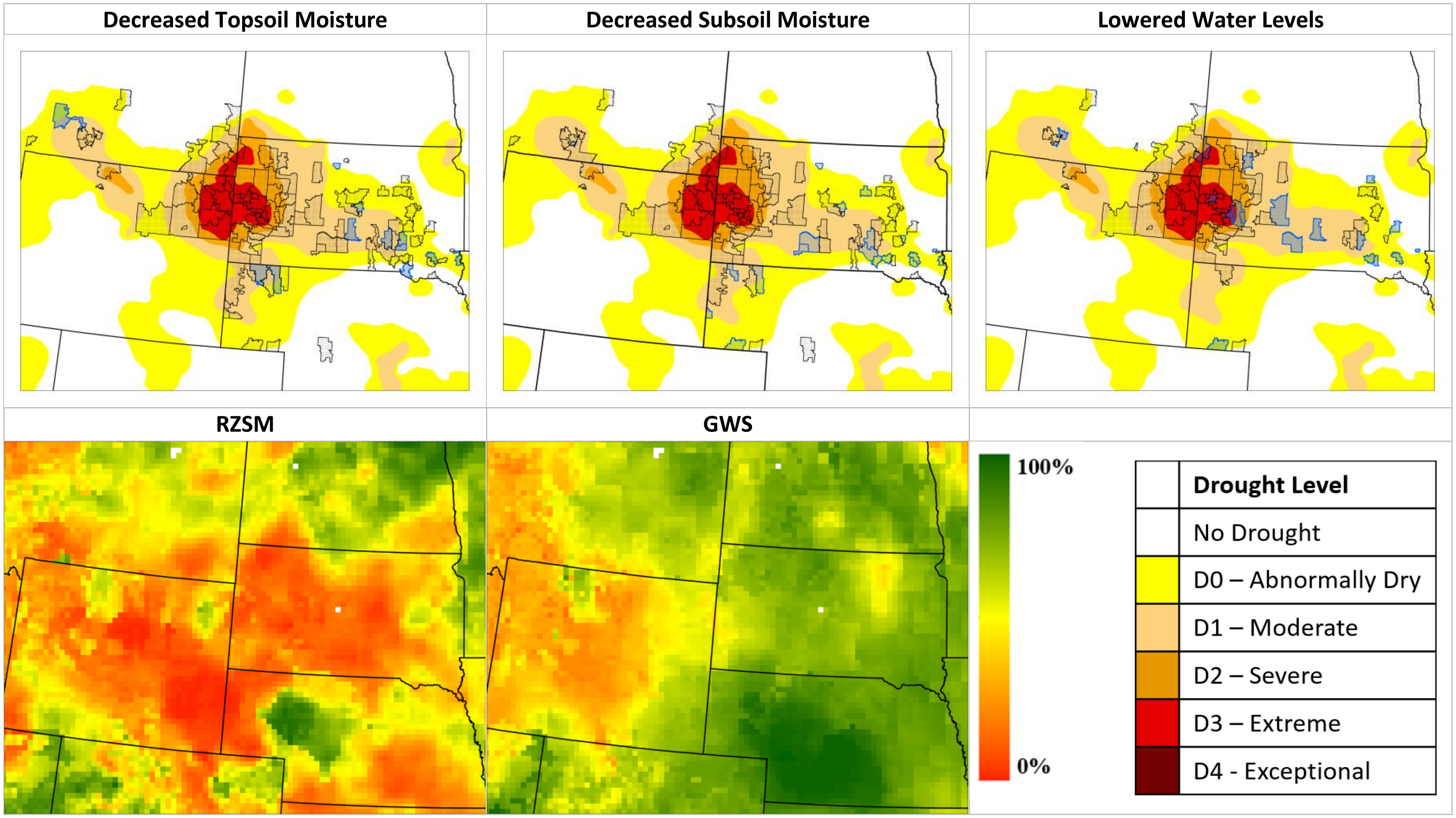

Figure 19 – Same as Figure 14 but all images valid 31 July 2016

August

The month of August saw some improvements in conditions around the core drought region, but still had some areas of D3 drought, and widespread areas of D2, D1, and D0. There were only a few new reports of decreased topsoil moisture (Fig 20) on the edges of the D0 conditions. A few more reports of decreased subsoil moisture also occurred, with a mix of within USDM drought and on the edge of drought areas. At this point, nearly all zip codes that had responses have indicated decreasing top and/or subsoil moisture, with the highest density of reports from within the core drought region of the South Dakota – Wyoming border. Additionally, there were more reports of lowered water levels, again mostly across South Dakota and close to D0 and D1 USDM areas.

At this point GRACE RZSM had substantial improvement in conditions across nearly the whole region, with some areas of Wyoming with very low soil moisture. This trend generally agrees with the lack of or lower number of reports of decreasing soil moisture conditions, even if the area is still generally dry. It is during this month, GRACE GWS percentiles were at their lowest average point over South Dakota, Nebraska, Wyoming, and Montana, with the state of Wyoming experiencing far lowered water levels. South Dakota sees little change from the previous month. This indicates some sort of disparity between the lowered water level reports and GWS percentiles.

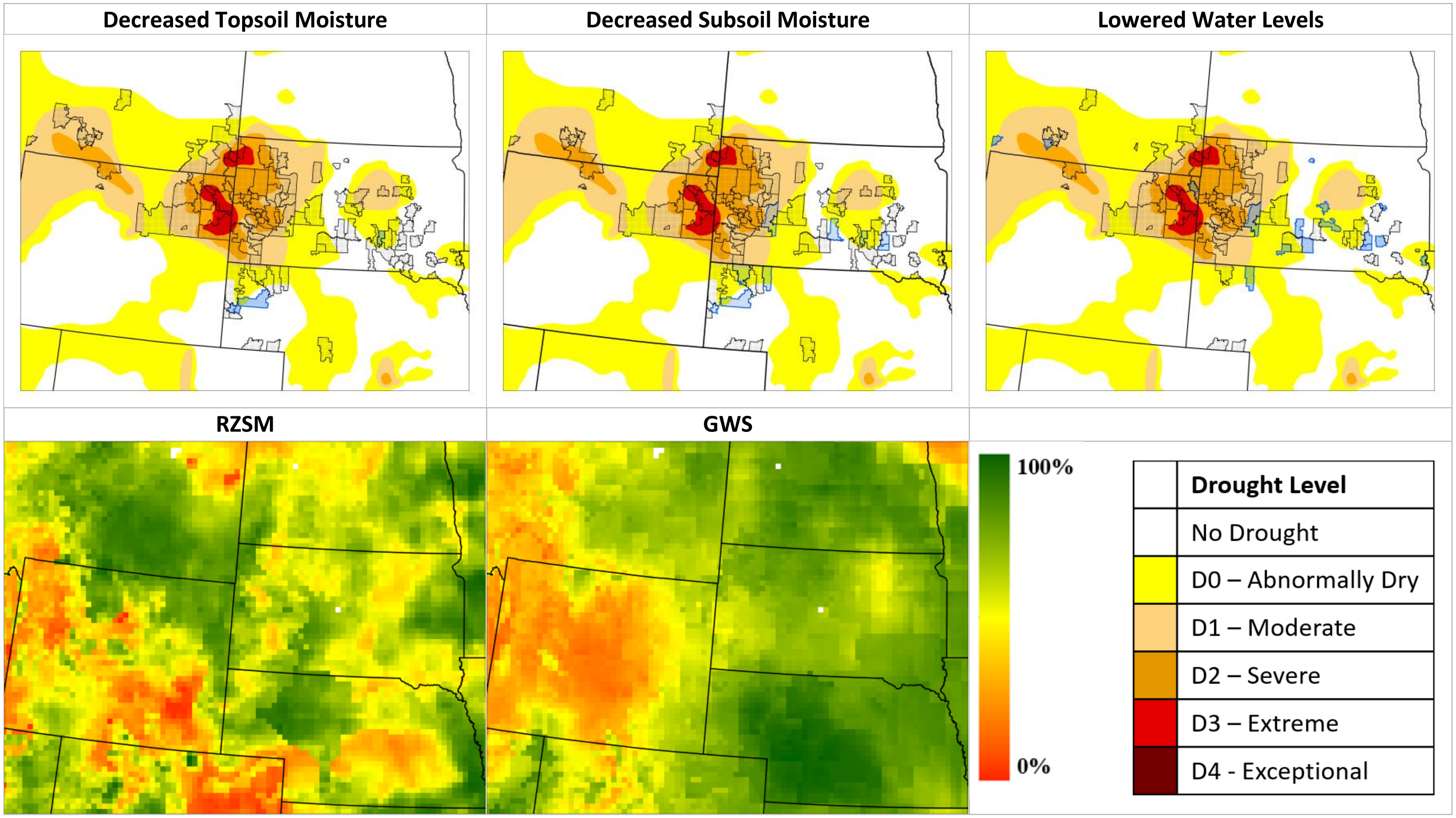

Figure 20 – Same as Figure 14 but all images valid 31 August 2016

3.3.2 Time-Series Comparison

This section assesses the evolution of the drought datasets in a 12-week period surrounding the date at which a respondent reported the specific conditions. For each individual survey response RZSM and GWS percentiles, and USDM drought level rasters were averaged by week over the respondent's zip code from 6 weeks prior to 6 weeks after the date of first occurrence of each condition. This averaging gives 348 individual trends for each condition. These individual trends were all averaged together, with the date of first occurrence of each condition centered on week zero.

Figure 21 indicates that at the time decreased topsoil moisture was first noted, RZSM had been steadily decreasing for up to 5 weeks, and USDM for up to 3 weeks previous. As this figure is averaged over all zip codes, the spatial pattern may not be homogenous, but in most areas, there is a signal of deteriorating conditions prior to stakeholders noting those conditions. RZSM starts at ~80% and decreases to ~40%, which by itself does not correspond to the D0 USDM drought category, but the deterioration is still a strong signal. This figure also indicates a signal is present in RZSM before USDM detects it.

Figure 22 shows the same process for decreased subsoil moisture. A similar trend is found where both RZSM and USDM detect a dryness signal before stakeholders. As in Figure 21, RZSM signals do not go into low percentiles, and vacillate between 40-50%. Figure 23 looks at the signal for lowered groundwater levels. As seen in the monthly comparisons, GRACE GWS showed a very gradual deterioration, which is evident in the graph. Six weeks prior to stakeholders observing lowered water levels, GWS was near

80% levels on average, and has a stead decreasing trend. Throughout the 12 weeks, GWS levels lowered on average ~10%. A similar trend occurs with RZSM, where the end percentile is not included in a drought category, but the trend is the main focus.

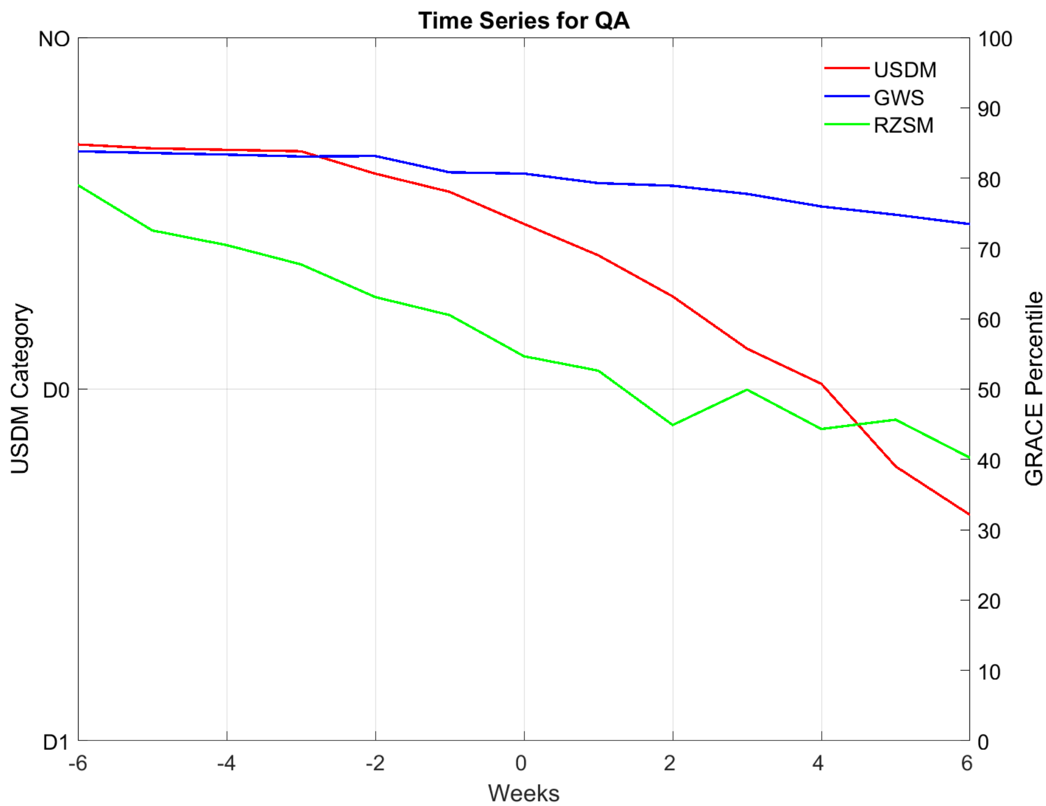

Figure 21 – Time series average values six weeks prior to six weeks after reports of first occurrence of decreased topsoil moisture. Left axis is average value of USDM drought category over each zip code. Right axis is average value of GWS and RZSM percentiles over each zip code. Left and right axes do not correspond to each other nor to associated drought level percentiles in Table 1.

Figure 22 – Same as Figure 21, but with reports of first occurrence of decreased subsoil moisture

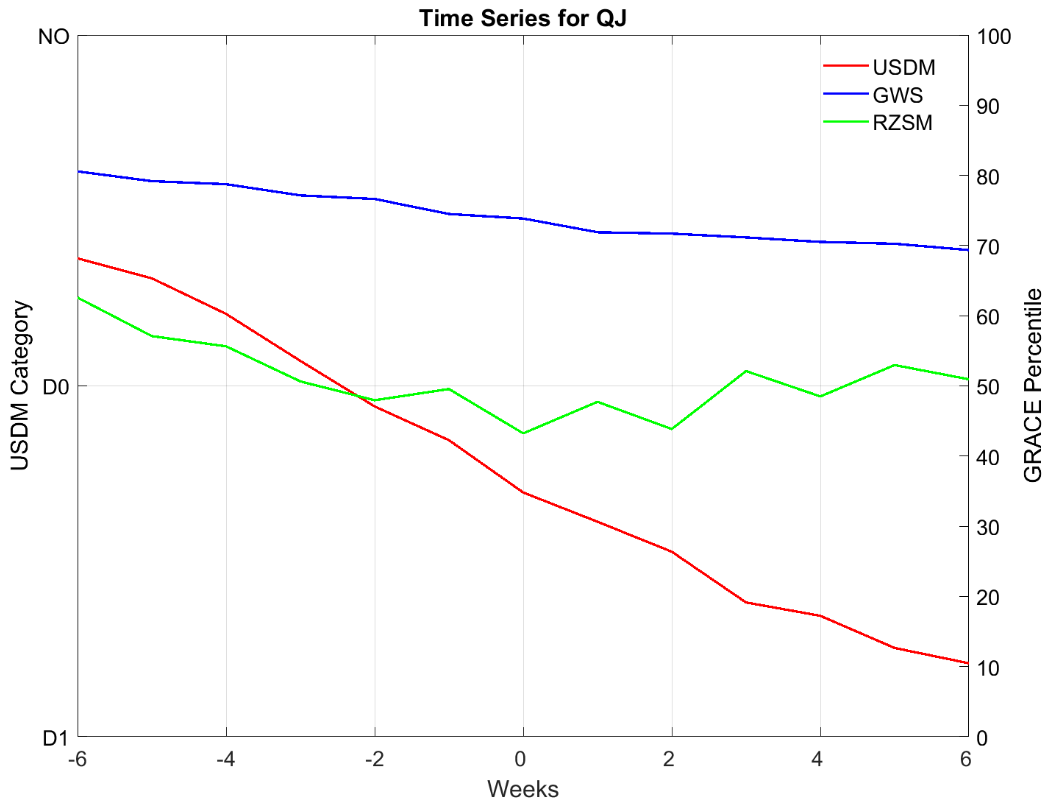

Figure 23 – Same as Figure 21, but with reports of first occurrence of lowered water levels in streams, ponds, or other water sources

CHAPTER 4 – DISCUSSION

4.1 Groundwater Well Comparison

The overall poor correlations for the well-GRACE comparisons indicates that GRACE GWS does not accurately reflect historic groundwater levels at this spatial resolution. This comparison and interpreting the results from both data sources is challenging because of the different timeframes each dataset used. Because the GRACE data assimilation uses the Catchment LSM and ranks current GWS percentiles based on the 1948-2009 levels, the historic data record is much longer than the well level period of record. A few USGS wells had historic records going back into the 1970's, but on average they started in the 1990's. The RTMN had even shorter periods of record, starting around 2009, which severely limits their historic rank accuracy. However, it seems that period of record does not determine correlation strength as demonstrated in Figure 24. Even wells with short histories may have strong negative correlations (negative in this comparison would indicate the same trend), and correlation strength is highly variable with record length. Even with these limitations, the dramatic variability in correlation values from well to well, indicates that there is some information contained within GRACE GWS, but it does not represent local, point-based well levels. One reason for this difference may be the differing spatial scales. Well observations are point measurements, while GRACE GWS is a single value over 190 km^2 area. The GRACE values representing an area averaged value may not always reflect the local well observations. Some wells have strong enough correlations to be considered significantly different than zero – agreeing with the conclusion that there is good information contained within the GRACE dataset. Even if the percentiles were off, the increasing or decreasing trend would allow for stronger correlations than were observed.

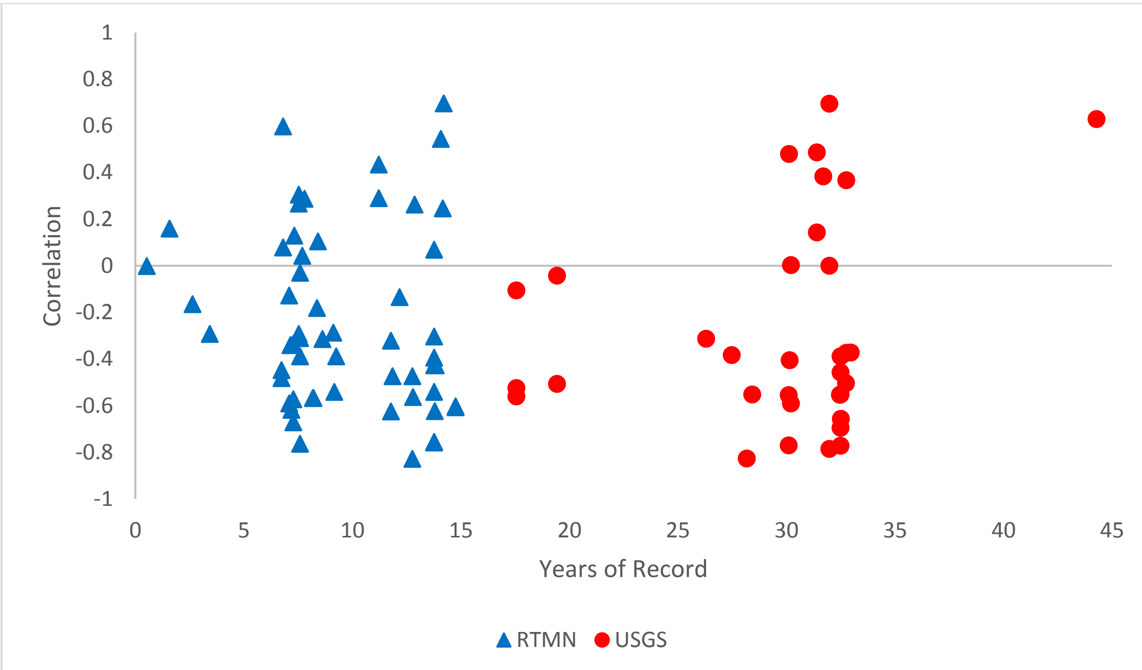

Figure 24 – Individual well correlation values and their respective periods of record for both USGS (red circle) and RTMN (blue triangle) well datasets.

Additionally, correlations between well levels (converted to USDM drought levels using the percentiles in Table 2) showed weak or negative correlations with USDM drought levels. This result was just a simple comparison that did not take into account the potential time-lag between GWS and USDM data. Because of this result, it is clear that raw well level data, or even data converted to historic percentile, when not accounting for time lag, is not on its own a good drought indicator. While GRACE GWS percentiles do not accurately represent groundwater levels from a drought monitoring perspective because it may still contain useful land surface information that correlates well to drought.

The spatial distribution of the correlations does not appear to directly correspond to major aquifer type as the vast majority of Nebraska land is above the High Plains aquifer, an unconsolidated sand and gravel aquifer. While many of the better (more negative) correlations appear along the Platte River, an area with high irrigation density, upon closer inspection the better correlations do not appear to be associated directly with more irrigated land. Figure 25 overlays the irrigated land with the correlation values. This irrigation dataset was produced by USGS with MODIS imagery for the year 2012 at 250m resolution (USGS, 2015). The higher density irrigation near the south-central part of the state around the Platte River does see good correlations, however, in other areas where there is significant irrigation, correlations are far poorer, specifically in the southwestern corner of the state. Additionally, throughout the Sandhills, northwestern – northern part of the state, where there is little or no irrigation, correlations range from -.80 to 0.4.

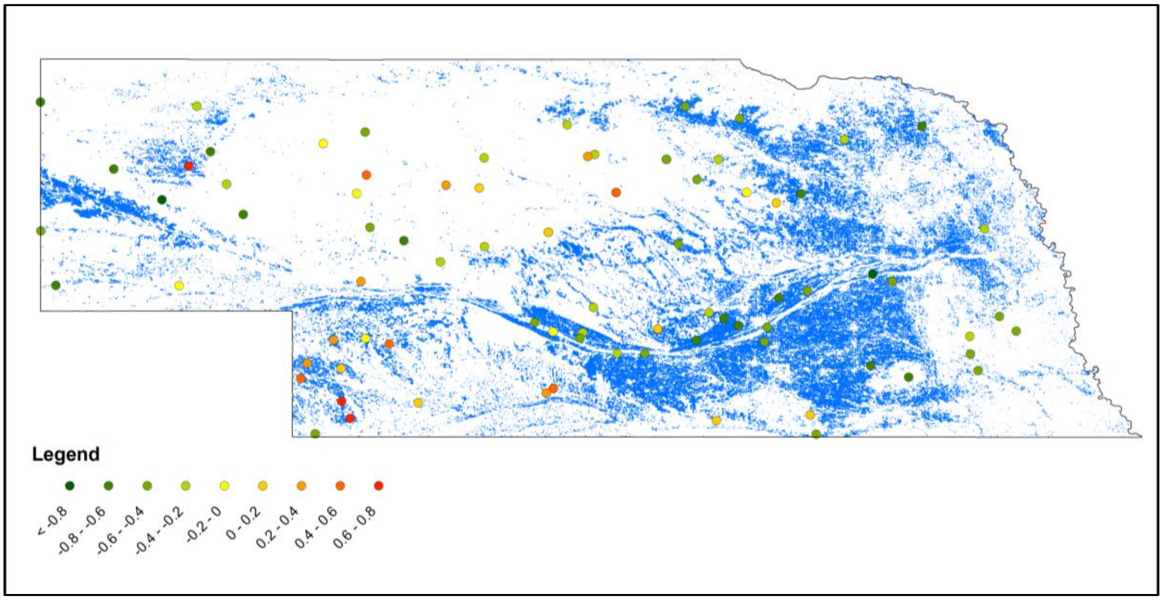

Figure 25 – Spatial distribution of individual well correlation values with irrigation density overlaid.

4.2 Spatial Correlations

4.2.1 GRACE-USDM

The conversion of GRACE percentiles into drought levels causes a significant loss of information. The six-decimal precision of the original GRACE percentile (accuracy not withstanding) is grouped into five categories. All the variation within groups is lost, including all high levels of groundwater and soil moisture (no drought corresponding to the largest percentile range) and only the transition from one category to another is analyzed with this correlation. Using these drought levels is necessary, however, because of the inherent uncertainty when authoring the USDM. These levels also are triggers for certain emergency responses in the United States, such as disaster declaration and relief funding. In addition to the loss of information from the reclassification of GRACE data, the GRACE drought levels revealed some areas of the

U.S. that have never experienced less than 30% dryness in GRACE GWS and RZSM historical data record. This led to the entire time series for pixels to be constant (-1). Because some covariance is required to calculate correlation, these areas are filled with NODATA values, again losing some additional information.

Overall, both GRACE GWS and RZSM showed strong, but not perfect correlations with USDM. GWS-USDM showed a stronger relationship than RZSM, although there was less spatial variability with RZSM-USDM. Because of the significant and positive relationship between these GRACE products and USDM, there is valuable drought monitoring information contained within GRACE products.

Moving from the complete time series to the seasonal comparisons, it is clear GRACE GWS has more agreement during JJA and SON, than MAM and DJF. RZSM performed better as a DI (higher agreement with the gold standard of drought indicators, USDM) during JJA, but not as notable a difference as with GWS. There were also distinct decreases in correlations over mountainous areas during winter months. This lends itself to a hypothesis that precipitation amount and precipitation type may influence performance of RZSM as a drought indicator. Mountainous areas also have generally shallow, poorly characterized soil moisture and groundwater estimates which may have led to a disconnect between GRACE products and drought characterization in these areas.

Generally individual pixel correlations for all comparisons ranged from greater than 0.90 to just above zero, but there is certainly a spatial pattern associated with it. Certain factors can be immediately removed as possible causes of this pattern such as altitude, irrigation, and precipitation, because they do not follow the same patterns as higher and lower correlated areas. A possible explanation for areas not experiencing strong agreement is the previously mentioned loss of information both from no covariance, as well as no variation within drought levels and inherent errors in the models and observation measurements.

In the analysis of whether GRACE datasets and USDM are independent, that is, did the Drought Monitor authors use GRACE data when deciding areas of drought, the correlations of data only through 2012 resulted in a slightly higher average correlation value for both GWS and RZSM. This indicates the general trend was not affected by any use of GRACE data for USDM. The major areas where the full timespan had higher correlations were typically those that saw extreme droughts post-2012 such as California. This additional change in drought level provides more trends to correlate with. While the possibility still exists that Drought Monitor authors used GRACE data, this study shows any overall impact was generally minor and regional.

As briefly discussed with USDM data, this research did not separate drought impacts and drought levels into “Short-term” and “Long-term”. Not distinguishing between these time-scales does limit the conclusion of this research. Logically, long-term drought designations would better correlate with groundwater, where short-term drought designations would correlate higher with soil moisture.

4.2.2 GRACE – SPI

The comparison of different accumulation periods of SPI and GRACE GWS and RZSM indicated a logical increase of correlation as the accumulation period increased up to a maximum, for GWS up to 0.543 and for RZSM up to 0.585. GWS logically takes longer to react to precipitation changes than RZSM and shows the highest correlations with longer accumulation periods, around 9-11 months. This timeline is in agreement with Fiorillo et al. (2010), which states springtime river discharge is best correlated with SPI at 9- to 12-month accumulation periods. The pattern of correlations may be explained simply by the amount of time precipitation takes to enter groundwater. Different geologic formations and aquifer types impact this amount of time.

RZSM shows very quick response to precipitation on the order of 2-5 months. There is less of a spatial pattern in these comparisons, potentially due to the quicker and more direct influence of precipitation on soil moisture. It is also important to note the RZSM – 3-month SPI showed the highest agreement at 0.585. This very high agreement with a well-known and widely used drought indicator shows strong promise for GRACE RZSM as a routine drought indicator.

Seasonality of GWS-SPI comparisons show us that both DJF and JJA hold similarly high correlations, whereas the transition seasons of MAM and SON have slightly lower correlations. A reason these differences are not strong may be because the minimum 9-month accumulation period obscures the original precipitation season. Liquid precipitation would enter groundwater faster than frozen, but the 9-month SPI will allow for seasonal frozen precipitation to melt and enter the groundwater system.

RZSM-SPI seasonal comparisons show significantly more seasonality with JJA agreeing most strongly with 2-5-month SPI. Because frozen precipitation takes longer to impact soil moisture than liquid precipitation, the winter DJF months have lower correlations. The spatial pattern is also consistent with this precipitation type theory, and DJF months show near zero or even slightly negative correlations over the high Rocky Mountains at all four accumulation periods.

4.2.3 GRACE – NLDAS

The three NLDAS model comparisons showed significant agreement with GRACE RZSM. As these comparisons are simply assessing where/when similar LSMs produce the same trends, the resulting high correlations were mostly expected. Differences that appeared mostly in the western U.S. could be a result of different topographic calculations between the Catchment LSM and NLDAS LSMs. Possible explanations could be rock/aquifer type or different observation densities. While the patterns also do not strictly match U.S. aquifers, the different physical characteristics of those aquifers may have a significant impact on the remote sensing and modeling aspect of GRACE data. Additionally, because this dataset is an LSM with extra data assimilated, the Catchment LSM may have observing or modeling bias in certain regions or may perform better with certain precipitation types.

The warmer months of JJA and SON produced the highest correlations in all three models. An explanation similar with the SPI correlations could also be at play here, that is, frozen precipitation. These NLDAS models may parameterize the melting and infiltration of snow differently to Catchment, so areas with high amounts of snow, specifically in winter months would have less overall agreement.

4.3 2016 Northern Plains Flash Drought

The examination of this specific flash drought event through the perspective of stakeholders in the region provides impact-based timelines of events that were compared to GRACE drought products. The ability of these products to match stakeholder observations, as well as other drought indicators such as USDM, should be a strong basis on which to decide what drought information to look at or include for decision makers.

The survey responses revealed this drought was comprised of a rapid decrease in both topsoil and subsoil moisture, increasing plant stress and death, followed by lowered water levels in ponds, streams, and wells. The USDM analysis showed many reports of drought conditions occurred near the time those areas were put into D0 or higher drought conditions. Several months saw a large number of reports early in the season before any widespread drought had reached those areas in the USDM. So, on monthly or longer time-scales, USDM and stakeholder reports generally agreed, the first occurrence of drought conditions were almost always preceding any USDM drought classification. In this region, drought is a typical part of the climate, and dryness happens relatively often. Based on the USDM drought percentile classifications, certain drought conditions, such as decreased soil moisture may appear before the “historic” dry points are reached.

In the month-to-month analysis GRACE RZSM matched relatively well with the USDM classifications. The overall trend into dry conditions was spatially and temporally captured across the region. RZSM percentiles dropped below 10% across much of the core drought region by the end of June, which correctly corresponds to D2 – D3 drought severity. Stakeholder observations of decreased topsoil and subsoil moisture also agreed with month to month GRACE RZSM decreases.

GRACE GWS proved a slowly changing indicator in this drought event. Throughout the drought event, GWS percentiles did not change quickly by jumping from higher percentiles one month to moderate or low percentiles the next, but instead gradually decreased across the region over many months. Many areas, including the core drought region, did end up with GWS percentiles near the 30% threshold for USDM D0 classification. GRACE GWS likely does not match the changes in stakeholder observations and USDM classifications because of the short nature of this event. Even with the generally poor performance of GWS for this specific event, the overall trend of declining groundwater was captured, just over longer timescales. This still allows for GWS percentiles to be used as a long-term drought indicator.

The quantitative analysis of zip code averaged drought indicator values, surrounding the date of first occurrence for the three drought conditions revealed that both USDM and GRACE RZSM picked up on deteriorating conditions long before the observations. The lowering of GRACE percentiles may not reach any thresholds before an observation was made, but the trend, if picked up by decision makers, could be used as early warning for flash drought events. For both topsoil and subsoil moisture GRACE RZSM shows declining trends over a month in advance and continues to deteriorate after observations were made. These soil moisture percentiles also started relatively high, near

80%, and the 12 weeks of worsening conditions halved that, showing a significant amount of dryness occurring.

A similar, but slower, trend is found with GRACE GWS percentiles. From 6 weeks prior to 6 weeks after first observations of lowered water levels, GWS continued on a steady decline from ~80% to ~70%. This timeframe corresponded to rapid intensification of drought as characterized by USDM. Because this slow trend was relatively weak, its use as a way to pinpoint drought areas is lessened.

CHAPTER 5 – CONCLUSIONS

This research used several comparison methods with observed, modeled, surveyed and professionally authored data to compare to GRACE GWS and RZSM percentile maps. In general, GRACE data showed some correlation with these datasets, meaning GRACE contains drought information and can provide necessary and timely information to decision makers about drought onset and severity.

The observed well data of USGS and RTMN compared relatively poorly with GWS, showing an expected average negative, but highly variable correlation [$-0.826 < r < 0.696$]. This result coupled with previous studies of larger scale resolution GRACE data (Zaitchik et al. 2008, Houborg et al. 2012) conclude historic GRACE GWS percentiles are far from perfect accuracy. These poor correlations with observed data may be explained by variable geologic and hydrologic formations, different densities in model observation data assimilation, as well as general inaccuracies in model parameters that determine groundwater levels.

Through the raster correlation comparisons, it was clear both GWS and RZSM data contain drought information also found in other DI datasets. Averaged over CONUS, correlations were positive, indicating good agreement, and significantly different than zero. Many times, these correlations had a spatial and seasonal pattern that likely results from how the different compared datasets deal with precipitation and groundwater infiltration. Seasonality could also come into play when decision makers are using these data, potentially putting more trust during the summer, JJA season, where agreement was higher.

By comparing to stakeholder observations during a flash drought event, it was found that GRACE RZSM provides a very similar picture of drought conditions and drought levels as determined by USDM. Additionally, RZSM can provide early warning to quick onset droughts if the data is presented in graphical form. GRACE GWS successfully signaled lowering of water levels during this drought event, but the spatial and graphical patterns were slow and limited for quick onset decisions. The GWS levels respond better and would be more useful in determining the extent and severity of longer duration drought events.

Through remote sensing data assimilation and modeling, GRACE GWS and RZSM percentiles have proven to be useful drought indicators and tools that can benefit stakeholders and decision makers by providing, weekly, regional scale maps of soil moisture and groundwater trends.

5.1 Future Work

There are several areas where future work regarding the GRACE percentile products should be considered. First, this study only assessed the accuracy of the GWS percentile products and evaluating the accuracy of the RZSM percentiles is equally important. Using regional, temporally continuous soil moisture networks, one can compare observed data to GRACE percentiles to determine if the trends match. Another area to further research is determining if aquifer type has an effect on GWS product accuracy. This study did not separate confined and unconfined aquifers due to low sample size, but any significant differences in accuracy found could help determine where GRACE GWS estimates are more accurate.

Finally, another topic to investigate further would be the disagreement between GRACE RZSM and NLDAS soil moisture, specifically over the Rocky Mountains. As previously discussed, GRACE gravity data is the only observational forcing difference between the NLDAS and Catchment LSMs, so it is possible this additional data assimilation may be resulting in more accurate soil moisture estimates. However, in order to determine if they are indeed more accurate, in situ soil moisture observations in that region will nee to be collected and compared to both NLDAS and GRACE soil moisture data. A significant improvement in soil moisture estimates would help stakeholders and decision makers in those regions to work with the most accurate data available.

References

Alley, W. M. (1984). The Palmer drought severity index: limitations and assumptions. *Journal of climate and applied meteorology, 23*, 1100-1109.

Brown, J. F., Wardlow, B. D., Tadesse, T., Hayes, M. J., & Reed, B. C. (2008). The Vegetation Drought Response Index (VegDRI): A new integrated approach for monitoring drought stress in vegetation. *GIScience & Remote Sensing, 45*, 16-46.

Croux, C., & Dehon, C. (2010). Influence functions of the Spearman and Kendall correlation measures. *Statistical methods & applications, 19*, 497-515.

Denmead, O. T., & Shaw, R. H. (1962). Availability of Soil Water to Plants as Affected by Soil Moisture Content and Meteorological Conditions 1. *Agronomy journal, 54*, 385-390.

Dillman, D. A., Phelps, G., Tortora, R., Swift, K., Kohrell, J., Berck, J., & Messer, B. L. (2009). Response rate and measurement differences in mixed-mode surveys using mail, telephone, interactive voice response (IVR) and the Internet. *Social science research, 38*, 1-18.

Ducharne, A., Koster, R. D., Suarez, M. J., Stieglitz, M., & Kumar, P. (2000). A catchment-based approach to modeling land surface processes in a general circulation model: 2. Parameter estimation and model demonstration. *Journal of Geophysical Research: Atmospheres, 105*, 24823-24838.

Fiorillo, F., & Guadagno, F. M. (2010). Karst spring discharges analysis in relation to drought periods, using the SPI. *Water resources management, 24*, 1867-1884.

Forman, B. A., Reichle, R. H., & Rodell, M. (2012). Assimilation of terrestrial water storage from GRACE in a snow-dominated basin. *Water Resources Research, 48*.

Heim Jr, R. R. (2002). A review of twentieth-century drought indices used in the United States. *Bulletin of the American Meteorological Society, 83*, 1149-1165.

Houborg, R., Rodell, M., Li, B., Reichle, R., & Zaitchik, B. F. (2012). Drought indicators based on model-assimilated Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage observations. *Water Resources Research, 48*.

Koster, R. D., & Suarez, M. J. (1992). Modeling the land surface boundary in climate models as a composite of independent vegetation stands. *Journal of Geophysical Research: Atmospheres, 97*, 2697-2715.

Koster, R. D., Suarez, M. J., Ducharne, A., Stieglitz, M., & Kumar, P. (2000). A catchment-based approach to modeling land surface processes in a general circulation model: 1. Model structure. *Journal of Geophysical Research: Atmospheres, 105*, 24809-24822.

Kumar, S. V., Zaitchik, B. F., Peters-Lidard, C. D., Rodell, M., Reichle, R., Li, B., . . . others. (2016). Assimilation of gridded GRACE terrestrial water storage estimates in the North American Land Data Assimilation System. *Journal of Hydrometeorology, 17*, 1951-1972.

Liang, X., Wood, E. F., & Lettenmaier, D. P. (1996). Surface soil moisture parameterization of the VIC-2L model: Evaluation and modification. *Global and Planetary Change, 13*, 195-206.

McKee, T. B., Doesken, N. J., Kleist, J., & others. (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology*, *17,* pp. 179-183.

Mitchell, K. E., Lohmann, D., Houser, P. R., Wood, E. F., Schaake, J. C., Robock, A., . . . others. (2004). The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system. *Journal of Geophysical Research: Atmospheres, 109*.

Niu, G.-Y., Seo, K.-W., Yang, Z.-L., Wilson, C., Su, H., Chen, J., & Rodell, M. (2007). Retrieving snow mass from GRACE terrestrial water storage change with a land surface model. *Geophysical Research Letters, 34*.

Niu, G.-Y., Yang, Z.-L., Mitchell, K. E., Chen, F., Ek, M. B., Barlage, M., . . . others. (2011). The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. *Journal of Geophysical Research: Atmospheres, 116*.

Otkin, J. A., Anderson, M. C., Hain, C., Mladenova, I. E., Basara, J. B., & Svoboda, M. (2013). Examining rapid onset drought development using the thermal infrared--based evaporative stress index. *Journal of Hydrometeorology, 14*, 1057-1074.

Palmer, C. W. (1965). Meteorological drought. *US Weather Bureau research paper*.

Rodell, M., Chen, J., Kato, H., Famiglietti, J. S., Nigro, J., & Wilson, C. R. (2007). Estimating groundwater storage changes in the Mississippi River basin (USA) using GRACE. *Hydrogeology Journal, 15*, 159-166.

Rouse Jr, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS.

Rowlands, D. D., Luthcke, S. B., Klosko, S. M., Lemoine, F. G., Chinn, D. S., McCarthy, J. J., . . . Anderson, O. B. (2005). Resolving mass flux at high spatial and temporal resolution using GRACE intersatellite measurements. *Geophysical Research Letters, 32*.

Smith, A. B., & Katz, R. W. (2013). US billion-dollar weather and climate disasters: data sources, trends, accuracy and biases. *Natural hazards, 67*, 387-410.

Su, H., Yang, Z.-L., Dickinson, R. E., Wilson, C. R., & Niu, G.-Y. (2010). Multisensor snow data assimilation at the continental scale: The value of Gravity Recovery and Climate Experiment terrestrial water storage information. *Journal of Geophysical Research: Atmospheres, 115*.

Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., . . . others. (2002). The drought monitor. *Bulletin of the American Meteorological Society, 83*, 1181-1190.

Tallaksen, L. M., & Van Lanen, H. A. (2004). *Hydrological drought: processes and estimation methods for streamflow and groundwater* (Vol. 48). Elsevier.

Tapley, B. D., Bettadpur, S., Watkins, M., & Reigber, C. (2004). The gravity recovery and climate experiment: Mission overview and early results. *Geophysical Research Letters, 31*.

United States Drought Monitor (2016, 6). The United States Drought Monitor.

United States Geological Survey (2015, 4). The 2012 Moderate Resolution Imaging Spectroradiometer (MODIS) Irrigated Agriculture 250-Meter Dataset for the Conterminous United States (MIrAD-US). Retrieved from https://earlywarning.usgs.gov/USirrigation

University of Nebraska-Lincoln Institute of Agriculture & Natural Resources (2017). Nebraska Real-Time Monitoring Network.

Wahr, J., Molenaar, M., & Bryan, F. (1998). Time variability of the Earth's gravity field: Hydrological and oceanic effects and their possible detection using GRACE. *Journal of Geophysical Research: Solid Earth, 103*, 30205-30229.

Wilhite, D. A. (2000). Drought as a natural hazard: concepts and definitions.

Wilhite, D. A., & Glantz, M. H. (1985). Understanding: the drought phenomenon: the role of definitions. *Water international, 10*, 111-120.

World Meteorological Organization (2012). *Standardized Precipitation Index User Guide (M. Svoboda, M. Hayes and D. Wood).* Geneva.

Xia, Y., Ek, M., Wei, H., & Meng, J. (2012). Comparative analysis of relationships between NLDAS-2 forcings and model outputs. *Hydrological Processes, 26*, 467-474.

Xia, Y., Mitchell, K., Ek, M., Cosgrove, B., Sheffield, J., Luo, L., . . . others. (2012). Continental-scale water and energy flux analysis and validation for North American Land Data Assimilation System project phase 2 (NLDAS-2): 2. Validation of model-simulated streamflow. *Journal of Geophysical Research: Atmospheres, 117*.

Yeh, P. J.-F., Swenson, S. C., Famiglietti, J. S., & Rodell, M. (2006). Remote sensing of groundwater storage changes in Illinois using the Gravity Recovery and Climate Experiment (GRACE). *Water Resources Research, 42*.

Zaitchik, B. F., Rodell, M., & Reichle, R. H. (2008). Assimilation of GRACE terrestrial water storage data into a land surface model: Results for the Mississippi River basin. *Journal of Hydrometeorology, 9*, 535-548.

Appendix I

Agriculture and the 2016 Drought

Dear Agricultural Producer,

Many areas of South Dakota, Wyoming, Montana, and Nebraska experienced drought conditions this year. We are conducting a survey to better understand when the drought began affecting farms and ranches, what the effects of the drought were, and how agricultural producers manage through drought. Results of this study will help drought researchers develop new tools to monitor agricultural drought conditions and inform the decisions you and other farmers make during drought.

We ask that this survey be completed by the person in your home that makes most of the farm management decisions and is at least 19 years old. If you did not experience drought conditions this year, we still want to hear from you! The survey should take approximately 20-25 minutes to complete, with no risk or discomfort. Your answers will be kept confidential and released only as summaries where individual answers cannot be identified.

☐ *If you are not an agricultural producer (e.g., you are a non-farming land owner), please check here and return in the envelope provided. We will remove you from our mailing list.*

You may choose to complete the enclosed paper version of the survey or take the survey online by entering the following website address into your web browser: **http://tinyurl.com/agdroughtsurvey**

If you choose to complete the survey online, you will need to enter the following code: The code is the letter "D" followed by a 4-digit number. This will let us know that you have completed the survey, so that we will stop sending you reminders.

CODE

You are free to decide not to participate in this study. You can also withdraw at any time without harming your relationship with the researchers or the University of Nebraska-Lincoln. If you choose not to participate, please let me know by mailing this letter back or by sending an email to thaigh2@unl.edu. Include the code and/or name and address on this letter in your email, and we will remove you from reminder mailings.

We value your input and your time, so we will be entering all returned surveys in a drawing for forty $25 VISA gift cards. You have approximately a 1-in-15 chance of receiving a gift card if you respond.

You may ask questions concerning this research at any time by contacting me by phone at 402-472-6781, or by email at thaigh2@unl.edu. If you would like to speak to someone else, please contact the Research Compliance Services Office at 402-472-6965 or irb@unl.edu.

Thanks so much!

Sincerely,

Tonya Haigh

Tonya Haigh
National Drought Mitigation Center
University of Nebraska-Lincoln
http://drought.unl.edu

Thank you in advance for sharing information about your experience with the 2016 drought, and your thoughts on drought risk management. Your answers to the first block of questions will help us develop more accurate drought monitoring tools in the future.

1. Did you experience drought conditions in 2016?
- ☐ No
- ☐ Yes
- ☐ I don't know

2. Are you currently experiencing drought conditions?
- ☐ No
- ☐ Yes
- ☐ I don't know

3. This question has two parts. First, with regard to drought over the past year, please indicate whether or not each of the following conditions occurred on your land. Then, if the condition occurred, tell us approximately when the condition first occurred during this drought.

	DID IT OCCUR THIS YEAR?				WHEN DID IT FIRST OCCUR?	
	NOT APPLICABLE	DID NOT OCCUR	OCCURRED		MONTH	DAY
A. Decreased topsoil moisture	☐	☐	☐	→		
B. Decreased subsoil moisture	☐	☐	☐	→		
C. Delayed or lack of plant emergence	☐	☐	☐	→		
D. Delayed or lack of plant growth	☐	☐	☐	→		
E. Plant stress (crop or pasture)	☐	☐	☐	→		
F. Plant death (crop or pasture)	☐	☐	☐	→		
G. Poor grain fill	☐	☐	☐	→		
H. Deteriorating range conditions	☐	☐	☐	→		
I. Decreased forage productivity	☐	☐	☐	→		
J. Lowered water levels in ponds, streams, or other water sources	☐	☐	☐	→		
K. Lack of water in ponds, streams, or other water sources	☐	☐	☐	→		
L. Wells unable to keep up with livestock or irrigation needs	☐	☐	☐	→		
M. Fire	☐	☐	☐	→		
N. Infestations of insects or other pests	☐	☐	☐	→		
O. Other: ______________	☐	☐	☐	→		

4. Please indicate whether or not you think that each of the following factors affected the timing and/or rate of drought development in your area this year.

	NO	YES	I DON'T KNOW
A. Lack of soil moisture going into winter	☐	☐	☐
B. Lack of snow cover	☐	☐	☐
C. Warm winter temperatures	☐	☐	☐
D. Early green up & plant growth	☐	☐	☐
E. Untimely killing frosts	☐	☐	☐
F. Other (please describe)	☐	☐	☐

5. When the drought was the most severe in 2016, how dry would you say it was on your farm or ranch?

- ☐ Less dry than it normally gets at that time of year
- ☐ About as dry as it normally gets at that time of year
- ☐ Drier than we've seen in the past 2-4 years
- ☐ Drier than we've seen in the past 5-10 years
- ☐ Drier than we've seen in the past 11-20 years
- ☐ Drier than we've seen for more than 20 years
- ☐ Drier than we've seen for 50 years
- ☐ Not sure

6. When the drought was the most severe in 2016, how hot would you say it was on your farm or ranch?

- ☐ Less hot than it normally gets at that time of year
- ☐ About as hot as it normally gets at that time of year
- ☐ Hotter than we've seen in the past 2-4 years
- ☐ Hotter than we've seen in the past 5-10 years
- ☐ Hotter than we've seen in the past 11-20 years
- ☐ Hotter than we've seen for more than 20 years
- ☐ Hotter than we've seen for 50 years
- ☐ Not sure

7. In your opinion, how likely is it that you could experience a drought as severe as 2016 again in the next 5 years?

- ☐ Very unlikely
- ☐ Somewhat unlikely
- ☐ Neutral
- ☐ Somewhat likely
- ☐ Very likely

Your answers to the next block of questions will help us better understand how drought affects agricultural operations in your area. The first section asks about livestock. If you do not raise livestock, please check ***No*** *below and skip to page 6.*

8. Do you raise livestock?

☐ No → **Please skip to page 6**

☐ Yes

9. Please indicate whether or not you raise each of the following types of livestock.

	NO	YES
A. Livestock registered seed stock	☐	☐
B. Beef cattle	☐	☐
C. Dairy	☐	☐
D. Sheep	☐	☐
E. Other (please describe):	☐	☐

10. Please indicate whether or not you use each of the following practices on rangeland that you manage.

	NO	YES
A. Feed livestock in a feedlot or dry lot during winter dormant season	☐	☐
B. Feed livestock in a feedlot or dry lot during summer growing season	☐	☐
C. Rotational or management intensive grazing	☐	☐

11. Please indicate whether or not you took each of the following actions on your farm in response to drought conditions in 2016. If yes, in what month did you begin taking each action?

	NOT APPLICABLE	NO	YES		BEGINNING IN WHAT MONTH?
A. Purchase more hay or feed than usual to supplement existing feed stocks	☐	☐	☐	→	
B. Graze fall or winter pastures earlier than planned	☐	☐	☐	→	
C. Destock pastures more than usual (through any culling, early weaning, ending grazing contracts, sending to feedlot, etc.)	☐	☐	☐	→	
D. Cull and sell more breeding animals than usual	☐	☐	☐	→	
E. Haul water to livestock more than usual	☐	☐	☐	→	
F. Lease additional pasture more than usual	☐	☐	☐	→	
G. Graze CRP land under CRP emergency haying and grazing program	☐	☐	☐	→	

12. How would you describe the effect of the 2016 drought for each of the following? If you experienced harm, what percentage of your yield or productivity would you estimate was lost?

	NOT APPLICABLE	NOT AT ALL HARMFUL	SLIGHTLY HARMFUL	MODERATELY HARMFUL	EXTREMELY HARMFUL	% OF YIELD OR PRODUCTIVITY LOST
A. Pasture hay yield	☐	☐	☐	☐	☐	
B. Range productivity	☐	☐	☐	☐	☐	
C. Range health or diversity	☐	☐	☐	☐	☐	
D. Animal reproduction	☐	☐	☐	☐	☐	
E. Animal gain/productivity	☐	☐	☐	☐	☐	
F. Other:	☐	☐	☐	☐	☐	

13. Is any of your pasture/range land irrigated or sub-irrigated?

☐ No
☐ Yes

14. If you manage range or pasture land, what percent is <u>currently</u> classified as excellent, good, fair, or poor range condition?

	Percent of all grazing land
a. **EXCELLENT** (considered vigorous, high production, high diversity of desirable grasses, broadleaf plants, and shrubs)	%
b. **GOOD** (vigorous, good production, moderate diversity of desirable grasses, broadleaf plants, and shrubs)	%
c. **FAIR** (stable but lower production, low diversity of desirable grasses, broadleaf plants, and shrubs)	%
d. **POOR** (low diversity, plant vigor, health, or productivity)	%

15. What percent was classified as excellent, good, fair, or poor range condition <u>prior to 2016</u>?

	Percent of all grazing land
a. **EXCELLENT**.	%
b. **GOOD**.	%
c. **FAIR**	%
d. **POOR**	%

The next section asks about row crops and hay. If you do not raise row crops or hay, please check ***No*** *below and skip to page 8.*

16. Do you raise row crops or alfalfa hay?

☐ No ➔ **Please skip to page 8**
☐ Yes

17. Please indicate whether or not you produce each of the following crops.

	NO	YES
A. Corn	☐	☐
B. Soybeans	☐	☐
C. Wheat (spring, winter, or durum)	☐	☐
D. Small grains (other than wheat)	☐	☐
E. Sorghum	☐	☐
F. Sunflowers	☐	☐
G. Sugar beets	☐	☐
H. Hay or forage crop	☐	☐
I. Other: ______________	☐	☐

18. Please indicate whether or not you use the following practices on farm- or rangeland that you manage.

	NO	YES
A. Cover crops	☐	☐
B. Drought tolerant varieties or hybrids	☐	☐
C. Any type of irrigation practice	☐	☐
D. Conservation irrigation practice (drop nozzles, drip, variable rate, etc.)	☐	☐
E. Conventional tillage	☐	☐
F. Reduced or Conservation tillage	☐	☐
G. No till	☐	☐

19. Approximately what percentage of land you plant to crops is considered drought-prone or sandy soil?

☐ 0 – 25 percent
☐ 26 – 50 percent
☐ 51 – 75 percent
☐ 76 – 100 percent

20. Please indicate whether or not you took each of the following actions on your farm in response to drought conditions in 2016. If yes, in what month did you begin taking each action?

	NOT APPLICABLE	NO	YES		BEGINNING IN WHAT MONTH?
A. Increase irrigation rate or length of season	☐	☐	☐	→	
B. Decrease tillage	☐	☐	☐	→	
C. Change grain marketing plans	☐	☐	☐	→	
D. Plant more acres of an alternative crop (including crops for forage or grazing livestock) than usual	☐	☐	☐	→	
E. Replant crops	☐	☐	☐	→	
F. Fallow more acres of land than anticipated	☐	☐	☐	→	
G. Adjust fertilizer rates	☐	☐	☐	→	
H. Adjust (decrease or increase) seeding rates	☐	☐	☐	→	
I. Plant more acres of drought resistant crop varieties than usual	☐	☐	☐	→	
J. Other (please describe)	☐	☐	☐	→	

21. **How would you describe the effect of the 2016 drought for each of the following? If you experienced harm, what percentage of your yield would you estimate was lost?** *Check one box per row.*

	NOT APPLICABLE	NOT AT ALL HARMFUL	SLIGHTLY HARMFUL	MODERATELY HARMFUL	EXTREMELY HARMFUL	% OF YIELD LOST
A. Corn yield	☐	☐	☐	☐	☐	
B. Winter wheat yield	☐	☐	☐	☐	☐	
C. Spring wheat yield	☐	☐	☐	☐	☐	
D. Soybean yield	☐	☐	☐	☐	☐	
E. Sunflower yield	☐	☐	☐	☐	☐	
F. Sorghum yield	☐	☐	☐	☐	☐	
G. Sugar beet yield	☐	☐	☐	☐	☐	
H. Alfalfa hay yield	☐	☐	☐	☐	☐	
I. Other (please describe)	☐	☐	☐	☐	☐	

The next section applies to all agricultural producers, and will help us better understand the financial impacts of drought.

22. In 2016, did you use cash contracts for selling crops or livestock (including forward contracts/fixed price, basis contracts, hedge-to-arrive contracts, etc.)?
- ☐ No
- ☐ Yes

23. If you raise either crops or livestock, please indicate whether or not you took each of the following actions on your farm in response to drought conditions in 2016. If yes, in what month did you begin taking each action?

	NOT APPLICABLE	NO	YES		BEGINNING IN WHAT MONTH?
A. Supplement farm income with new or increased off-farm work	☐	☐	☐	→	
B. Supplement farm income with new or increased on-farm enterprises	☐	☐	☐	→	

24. How would you describe the effect of the 2016 drought for each of the following? If you experienced harm, what percentage would you estimate was lost?

	NOT APPLICABLE	NOT AT ALL HARMFUL	SLIGHTLY HARMFUL	MODERATELY HARMFUL	EXTREMELY HARMFUL	% LOST
A. Net income of operation	☐	☐	☐	☐	☐	
B. Cash reserves or savings	☐	☐	☐	☐	☐	

25. In addition to your farming or ranching operation, does your operation generate income from any of the following on-farm enterprises? If yes, was drought in 2016 harmful to the enterprise?

	DO YOU GENERATE INCOME FROM THIS ENTERPRISE?			IF YES, WAS DROUGHT HARMFUL?	
	NO	YES		NO	YES
A. Hunting operation or agri-tourism operation	☐	☐	→	☐	☐
B. Custom field work and other agricultural services provided to others	☐	☐	→	☐	☐
C. Custom or contract grazing of livestock (animals run on your operation but not owned by you)	☐	☐	→	☐	☐
D. Payments received from cash rent or share	☐	☐	→	☐	☐
E. Other (please describe):	☐	☐	→	☐	☐

26. Please indicate whether or not you participated in each of the following programs for 2016.

	NO	YES

A. Any crop, livestock, range, forage, or revenue insurance program	☐	☐
B. Any federal conservation program or cost-share program (e.g., CRP, EQIP)	☐	☐
C. Other state, county, or local conservation program or cost-share program (please describe):	☐	☐

27. Will (or did) you receive a crop or livestock insurance payment because of the 2016 drought?

☐ No
☐ Yes

28. Will (or did) you receive a federal crop disaster assistance payment (not crop insurance) for 2016?

☐ No
☐ Yes

29. Please rate how certain you are that you can attain good results on your farm/ranch for each circumstance.

	NOT AT ALL CERTAIN	SOMEWHAT CERTAIN	MODERATELY CERTAIN	VERY CERTAIN	EXTREMELY CERTAIN
A. When precipitation and temperatures are normal	☐	☐	☐	☐	☐
B. When the whole year is <u>somewhat</u> dry	☐	☐	☐	☐	☐
C. When the whole year is <u>extremely</u> dry	☐	☐	☐	☐	☐
D. When it is dry for more than two years	☐	☐	☐	☐	☐
E. When the whole year is extremely wet	☐	☐	☐	☐	☐
F. When the whole year is extremely warm					
G. When crop commodity prices are low	☐	☐	☐	☐	☐
H. When livestock prices are low	☐	☐	☐	☐	☐
I. When input costs are high	☐	☐	☐	☐	☐

Your answers to the next block of questions will help us improve drought and climate information delivery, and identify needed resources and information.

30. Do you consult any of the following sources for information on drought conditions? If yes, how influential are they to your farming/ranching management decisions?

				IF YES, HOW INFLUENTIAL TO YOUR DECISIONS?		
	NO	**YES**		**NOT INFLUENTIAL**	**SOMEWHAT INFLUENTIAL**	**VERY INFLUENTIAL**
A. On-farm rain gauge or soil moisture sensors	☐	☐	→	☐	☐	☐
B. Own assessment of crop, range, or livestock conditions	☐	☐	→	☐	☐	☐
C. Friends or family	☐	☐	→	☐	☐	☐
D. State climatologist office	☐	☐	→	☐	☐	☐
E. Local extension	☐	☐	→	☐	☐	☐
F. National Weather Service	☐	☐	→	☐	☐	☐
G. U.S. Drought Monitor	☐	☐	→	☐	☐	☐
H. USDA resources	☐	☐	→	☐	☐	☐
I. Weather apps	☐	☐	→	☐	☐	☐
J. A farm advisor	☐	☐	→	☐	☐	☐
K. Television or radio weather reports	☐	☐	→	☐	☐	☐

31. If you had received information earlier that told you when the 2016 drought was <u>starting</u>, would you have acted earlier or differently than you did this year?

☐ No
☐ Yes
☐ I don't know

32. If you had received information earlier that told you when the 2016 drought was <u>getting worse</u>, would you have acted earlier or differently than you did this year?

☐ No
☐ Yes
☐ I don't know

33. If you had acted earlier or differently than you did this year, do you think you would have seen less harm to your operation?

☐ No
☐ Yes
☐ I don't know

34. Does your operation have specific actions that you plan to take when drought conditions occur (e.g., a "drought plan")?

- ☐ No
- ☐ Yes
- ☐ I don't know

35. Do you belong to any producers' organizations (such as Stockgrowers, Cattlemen's, Sheep Growers, Corn Growers, Wheat Producers, Western Sugar, etc.)?

- ☐ No
- ☐ Yes
- ☐ I don't know

36. Do you belong to any other farm/ranch educational organizations (such as Grasslands Coalition, Women in Farm Economics, sustainable farming organizations, no-till organizations, etc.)?

- ☐ No
- ☐ Yes
- ☐ I don't know

37. In the past year, have you attended any extension education programs, field tours, or other educational workshops on farm or ranch related issues?

- ☐ No
- ☐ Yes
- ☐ I don't know

38. Do you access the internet primarily on a desktop or laptop computer, tablet device, or cell phone? *Check one.*

- ☐ I do not have internet access
- ☐ Primarily on a desktop or laptop computer
- ☐ Primarily on a tablet device
- ☐ Primarily on a cell phone

To what degree would you consider each of the following a barrier to your ability to prepare for and deal with drought on your farm/ranch?

	NOT A BARRIER	SOMEWHAT OF A BARRIER	MODERATE BARRIER	EXTREME BARRIER
A. Information about the onset and severity of drought	☐	☐	☐	☐
B. Knowledge about how to reduce drought impacts on my farm/ranch	☐	☐	☐	☐
C. Technical skills to carry out specific practices on my farm/ranch	☐	☐	☐	☐
D. Financial resources to carry out specific practices on my farm/ranch	☐	☐	☐	☐

39. **Please rate how effective you think each of the following strategies are for lessening drought harm to farms/ranches in your area:**

	NOT AT ALL EFFECTIVE	SLIGHTLY EFFECTIVE	MODERATELY EFFECTIVE	VERY EFFECTIVE	EXTREMELY EFFECTIVE
A. Conservation tillage	☐	☐	☐	☐	☐
B. No-till	☐	☐	☐	☐	☐
C. Irrigation	☐	☐	☐	☐	☐
D. Rotation grazing	☐	☐	☐	☐	☐
E. Diversification of crops	☐	☐	☐	☐	☐
F. Integration of crops and livestock	☐	☐	☐	☐	☐
G. Building soil organic matter	☐	☐	☐	☐	☐
H. Planting drought-tolerant crops	☐	☐	☐	☐	☐
I. Conservative stocking rate	☐	☐	☐	☐	☐
J. Rotating crops	☐	☐	☐	☐	☐
K. Diversifying farm/ranch income sources	☐	☐	☐	☐	☐
L. Reducing farm/ranch debt	☐	☐	☐	☐	☐

40. **Please indicate your opinion on the following statements:**

A. The outcomes of my farm/ranch management during drought are…	**Completely uncontrollable** ☐	**Mostly uncontrollable** ☐	**Neutral** ☐	**Mostly controllable** ☐	**Completely controllable** ☐
B. Making farm/ranch decisions to minimize losses from drought is…	**Completely difficult** ☐	**Mostly difficult** ☐	**Neutral** ☐	**Mostly easy** ☐	**Completely easy** ☐

41. For each statement below, please indicate whether or not the statement describes you.

	DOES NOT DESCRIBE ME	DESCRIBES ME SLIGHTLY WELL	DESCRIBES ME MODERATELY WELL	DESCRIBES ME VERY WELL	DESCRIBES ME EXTREMELY WELL
A. I consider how my farm/ranch might look in the future when making day to day decisions	☐	☐	☐	☐	☐
B. I make decisions to achieve outcomes that may not occur for many years	☐	☐	☐	☐	☐
C. I focus on solving immediate problems, and let the future take care of itself	☐	☐	☐	☐	☐
D. I am focused on making decisions that affect the outcomes of this growing season	☐	☐	☐	☐	☐
E. Convenience is a big factor in the farm/ranch decisions I make	☐	☐	☐	☐	☐
F. I am willing to sacrifice immediate profit in order to achieve future success	☐	☐	☐	☐	☐
G. It is important to heed warnings about negative outcomes even if they will not occur for many years	☐	☐	☐	☐	☐
H. It is more important to focus on important future outcomes than on less important immediate concerns	☐	☐	☐	☐	☐
I. I am not concerned about future problems because I think they can be dealt with later	☐	☐	☐	☐	☐
J. I focus on decisions that affect me now, because I can take care of future problems later	☐	☐	☐	☐	☐
K. What happens on my farm/ranch this year is more important than what happens in the future	☐	☐	☐	☐	☐
L. When I make a decision, I think about how it might affect my farm/ranch in the future	☐	☐	☐	☐	☐
M. My management is generally influenced by future consequences	☐	☐	☐	☐	☐
N. I make farm/ranch decisions based on what other producers or experts recommend	☐	☐	☐	☐	☐
O. I make farm/ranch decisions based on my own experiences	☐	☐	☐	☐	☐
P. I believe that farm/ranch success is mostly due to luck	☐	☐	☐	☐	☐
Q. I learn from the challenges I experience	☐	☐	☐	☐	☐
R. I seek out new technologies to use on my farm/ranch	☐	☐	☐	☐	☐

The final block of questions provides demographic information. Your responses will help us understand how drought affects different types of agricultural producers, and what is needed to improve drought management.

42. Please indicate the total number of acres you own and rent from others that are crop land (including fallow land), range or pasture land, and hay land:

	NUMBER OF ACRES OWNED	NUMBER OF ACRES RENTED
a) Crop land (including fallow land)................		
b) Range or pasture land..................................		
c) Hay land..		

43. Please indicate the level of your gross farm/ranch sales in a typical year.

☐ Under $25,000
☐ $25,000 - $49,999
☐ $50,000 - $99,999
☐ $100,000 - $249,999
☐ $250,000 - $499,999
☐ $500,000 - $999,999
☐ $1,000,000 - $1,499,999
☐ $1,500,000 - $1,999,999
☐ $2,000,000 or more

44. Approximately what percentage of your gross farm/ranch sales is profit?

☐ 0 – 20 percent
☐ 21 – 40 percent
☐ 41 – 60 percent
☐ 61 – 80 percent
☐ 81 – 100 percent

45. In 2016, how many households shared in the net farm income of this farm/ranch operation?

_________ household(s)

46. In 2016, what percent of the principal operator's total household income came from the farm/ranch operation?

☐ 0 – 20 percent
☐ 21 – 40 percent
☐ 41 – 60 percent
☐ 61 – 80 percent
☐ 81 – 100 percent

47. What is the highest level of education that you have completed?
- ☐ Some formal education, less than high school
- ☐ High school/GED
- ☐ 2-year college/technical/Associate degree
- ☐ Four-year college degree (Bachelor's degree)
- ☐ Advanced degree (MS, MBA, PhD, etc.)

48. What is your age?
- ☐ 19-29
- ☐ 30-39
- ☐ 40-49
- ☐ 50-59
- ☐ 60-69
- ☐ 70 or over

49. For how many years have you been a primary decision maker for your farm/ranch?
- ☐ Fewer than 10 years
- ☐ 10 - 19 years
- ☐ 20 – 29 years
- ☐ 30 – 39 years
- ☐ 40 – 49 years
- ☐ 50 years or more

50. What is your gender?
- ☐ Male
- ☐ Female

51. Are you a member of a Native American Tribal Nation or of Native American heritage?
- ☐ No
- ☐ Yes
- ☐ I don't know

Thank you for your time and assistance!

Please use the space below for any additional comments about conditions in 2016.

Optional: Please use this space to let us know if any of the questions were confusing or difficult to answer. Your feedback is valuable to us.

Please return your completed questionnaire in the postage-paid envelope provided.

Tonya Haigh
National Drought Mitigation Center
3310 Holdrege Street
Lincoln NE 68583-0988

Appendix II

```
# ##
# Description: R code to calculate correlation coefficients between well and GRACE data
# Author: Anthony Mucia
# Date: May 2018
# Notes: Very basic table output, which is then manually transformed into useable formats
# to speed up
# ##

.libPaths("/Library/Path")
library(tidyverse)

## Reading in Data
USGSPerc <- read_csv("/Path/To/Data/USGSWellPercentiles.csv", na = "NA")
USGSWellDM <- read_csv("/Path/To/Data/USGSWellDM.csv", na = "NA")
graceUSGSPerc <- read_csv("/Path/To/Data/USGSGRACEPercentiles.csv", na = "NA")
graceUSGSPercC <- read_csv("/Path/To/Data/USGSGRACE_C_Percentiles.csv", na =
"NA")
USGSDM <- read_csv("/Path/To/Data/USGSDM.csv", na = "NA")

RTMNPerc <- read_csv("/Path/To/Data/RTMNWellPercentiles.csv", na = "NA")
RTMNWellDM <- read_csv("/Path/To/Data/RTMNWellDM.csv", na ="NA")
graceRTMNPerc <- read_csv("/Path/To/Data/RTMNGRACEPercentiles.csv", na =
"NA")
graceRTMNPercC <- read_csv("/Path/To/Data/RTMNGRACE_C_Percentiles.csv", na =
"NA")
RTMNDM <- read_csv("/Path/To/Data/RTMNDM.csv", na = "NA")

USGScols <- ncol(USGSPerc)
RTMNcols <- ncol(RTMNPerc)
usgscor <- 0
rtmncor <- 0

## Setting up column naming
for (i in 2:USGScols){
  names(usgscor[i]) <- names(USGSPerc[i])
}
for (i in 2:RTMNcols){
  names(rtmncor[i]) <- names(RTMNPerc[i])
}
as.data.frame(usgscor)
as.data.frame(rtmncor)
names(usgscor) <- names(USGSPerc)
```

```
names(rtmncor) <- names(RTMNPerc)

## Percentile - Percentile Correlation Calculations
for (i in 2:USGScols){
  usgscor[i] <- cor.test(USGSPerc[[i]], graceUSGSPerc[[i]], use =
"pairwise.complete.obs", method = "spearman")
}
for(i in 2:RTMNcols){
  rtmncor[i] <- cor(RTMNPerc[[i]], graceRTMNPerc[[i]], use = "pairwise.complete.obs",
method = "spearman")
}
write.table(usgscor, "/Path/To/Data/Out/usgsCor.csv", sep = ",", append = T)
write.table(rtmncor, "/Path/To/Data/Out/rtmnCor.csv", sep = ",", append = T)

## Percentile - Cubic Correlations
for (i in 2:USGScols){
  usgscor[i] <- cor(USGSPerc[[i]], graceUSGSPercC[[i]], use = "pairwise.complete.obs",
method = "spearman")
}
for(i in 2:RTMNcols){
  rtmncor[i] <- cor(RTMNPerc[[i]], graceRTMNPercC[[i]], use =
"pairwise.complete.obs", method = "spearman")
}
write.table(usgscor, "/Path/To/Data/Out/usgsCor.csv", sep = ",", append = T)
write.table(rtmncor, "/Path/To/Data/Out/rtmnCor.csv", sep = ",", append = T)

## Well DM Level - DM Level
for (i in 2:USGScols){
  usgscor[i] <- cor(USGSWellDM[[i]], USGSDM[[i]], use = "pairwise.complete.obs",
method = "spearman")
}
for(i in 2:RTMNcols){
  rtmncor[i] <- cor(RTMNWellDM[[i]], RTMNDM[[i]], use = "pairwise.complete.obs",
method = "spearman")
}
write.table(usgscor, "/Path/To/Data/Out/usgsCor.csv", sep = ",", append = T)
write.table(rtmncor, "/Path/To/Data/Out/rtmnCor.csv", sep = ",", append = T)
```

Appendix III

```
# ##
# Description: Python code to calculate correlation coefficients between two raster
datasets
# Author: Anthony Mucia
# Date: May 2018
# Notes: This code is based around a community answer by ESRI Community user
Xander Bakker
# https://community.esri.com/thread/200534-re-correlation-between-two-different-
rasters
# ##

def main():
    import arcpy, glob, winsound, os
    import numpy as np
    import numpy.ma as ma
    import pandas as pd
    arcpy.env.overwriteOutput = True
    dataPath1 = r'Input/Data_1/Folder'
    dataPath2 = r'Input/Data_2/Folder'
    L1 = glob.glob(dataPath1+'\*.tif')
    L2 = glob.glob(dataPath2+'\*.tif')

    nodata = -999
    out_ras = r'Output/Raster/Folder/output.tif'
    outDataPath = r'Output/Raster/Folder/'
    print("        List 1 Raster Count = "+str(len(L1)))
    print("        List 2 Raster Count = "+str(len(L2)))
    L1 = sorted(L1)
    L2 = sorted(L2)

    print "Creating arrays..."
    lst_np_ras = []
    for i in range(0, len(L1)):
        ras_path1 = L1[i]
        print " - ", ras_path1
        ras_np1 = arcpy.RasterToNumPyArray(ras_path1)
        ras_path2 = L2[i]
        print " - ", ras_path2
        ras_np2 = arcpy.RasterToNumPyArray(ras_path2)
        lst_np_ras.append([ras_np1, ras_np2])

    print "Reading numPy rasters..."
    ras_np = lst_np_ras[0][0]
    rows = ras_np.shape[0]
```

```
    cols = ras_np.shape[1]
    print " - rows:", rows
    print " - cols:", cols

    print "Creating output numPy array..."
    ras_path = L1[0]
    raster = arcpy.Raster(ras_path)
    ras_np_res = np.ndarray((rows, cols))
    ras_np_res2 = np.ndarray((rows, cols))
    print " - rows:", ras_np_res.shape[0]
    print " - cols:", ras_np_res.shape[1]

    print "Looping through pixels..."
    pix_cnt = 0
    for row in range(rows):
        for col in range(cols):
            pix_cnt += 1
            if pix_cnt % 5000 == 0:
                print " - row:", row, "  col:", col, "  pixel:", pix_cnt
            lst_vals1 = []
            lst_vals2 = []
            try:
                for lst_pars in lst_np_ras:
                    lst_vals1.append(lst_pars[0][row, col])
                    lst_vals2.append(lst_pars[1][row, col])
                lst_vals1 = ReplaceNoData(lst_vals1, nodata)
                lst_vals2 = ReplaceNoData(lst_vals2, nodata)
                correlation = SpearmanCorrelation(lst_vals1, lst_vals2, nodata)
                ras_np_res[row, col] = correlation
            except Exception as e:
                print "ERR:", e
                print " - row:", row, "  col:", col, "  pixel:", pix_cnt
                print " - lst_vals1:", lst_vals1
                print " - lst_vals2:", lst_vals2

    pnt = arcpy.Point(raster.extent.XMin, raster.extent.YMin)
    xcellsize = raster.meanCellWidth
    ycellsize = raster.meanCellHeight
    dsc = arcpy.Describe(L1[0])
    coord_sys = dsc.spatialReference

    print "Writing output raster..."
    print " - ", out_ras
    ras_res = arcpy.NumPyArrayToRaster(ras_np_res, lower_left_corner=pnt,
x_cell_size=xcellsize,
```

```
                         y_cell_size=ycellsize, value_to_nodata=nodata)
    ras_res.save(out_ras)
    arcpy.DefineProjection_management(in_dataset=out_ras, coor_system=coord_sys)
    print("Cleaning up work files...")
    FileCleanup(outDataPath)
    print ("Complete")

def FileCleanup(path):
    import os, glob, winsound
    file_name = os.listdir(path)
    for item in file_name:
      if item.endswith(".xml") or item.endswith(".tfw") or item.endswith(".ovr"):
         os.remove(os.path.join(path, item))
    winsound.Beep(1000,1000)

def PearsonCorrelation(a, b, nodata):
    import numpy
    try:
        coef = numpy.corrcoef(a,b)
        return coef[0][1]
    except:
        return nodata

def SpearmanCorrelation(a, b, nodata):
    import pandas as pd
    try:
        a = pd.Series(a)
        b = pd.Series(b)
        coef = a.corr(b,method = "spearman")
        return coef
    except:
        return nodata

def ReplaceNoData(lst, nodata):
    res = []
    for a in lst:
        if a == nodata:
            res.append(None)
        else:
            res.append(a)
    return res

if __name__ == '__main__':
    main()
```