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Article

Groundwater Level Changes Due to Extreme Weather—An Evaluation Tool for Sustainable Water Management

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Abstract: In the past decade, extreme and exceptional droughts have significantly impacted many economic sectors in the US, especially in California, Oklahoma, and Texas. The record drought of 2011–2014 affected almost 90% of Texas areas and 95% of Oklahoma state areas. In 2011 alone, around $1.6 billion in agricultural production were lost as a result of drought in Oklahoma, and $7.6 billion in Texas. The agricultural sectors in Oklahoma and Texas rely mainly on groundwater resources from the non-replenishable Ogallala Aquifer in Panhandle and other aquifers around the states. The exceptional droughts of 2011–2014 not only caused meteorologically induced water scarcity (due to low precipitation), but also prompted farmers to overuse groundwater to maintain the imperiled production. Comprehensive studies on groundwater levels, and thus the actual water availability/scarcity across all aquifers in Oklahoma and Texas are still limited. Existing studies are mainly focused on a small number of selected sites or aquifers over a short time span of well monitoring, which does not allow for a holistic geospatial and temporal evaluation of groundwater level variations. This paper aims at addressing those issues with the proposed geospatial groundwater visualization model to assess availability of groundwater resources for agricultural, industrial, and municipal uses both in Oklahoma and Texas in the time frame of 2003–2014. The model is an evaluation tool that can be used by decision-makers for designing sustainable water management practices and by teachers and researchers for educational purposes.

Keywords: drought; geospatial analysis; groundwater; US; visualization; water management

1. Introduction

Over the past centuries, extreme and exceptional drought events have significantly affected both surface water and groundwater resources [1–3]. While low surface water levels might be an immediate indicator of drought, changes to groundwater levels indicate long-term water scarcity. At the same time, while it is relatively straightforward to monitor and assess surface water changes, measuring variations in groundwater resources (aquifers) is very challenging and time consuming, which—in many cases—leads to missing or scattered data sets. However, while surface water resources can be replenished by adequate precipitation, groundwater aquifers might be non-replenishable once exploited (like, e.g., the Ogallala Aquifer containing fossil water, especially in the southern parts of the High Plains) [4] or it may take years for an aquifer to replenish naturally, subject to geological formations in different regions. While these conditions make groundwater resources extremely valuable, groundwater monitoring and measurements have been inconsistent geographically and over time.

This research aims at developing a model that can serve as an evaluation tool for variations in groundwater levels in two states, Oklahoma and Texas that have been mostly affected by the recent drought events. While the model presents a user-friendly way to analyze geographical and temporal variations in water availability in Oklahoma and Texas aquifers, it also sets a ground for our work on an integrated drought indicator to serve as a predictor of drought in the future. For the last decade, Texas and Oklahoma have been exposed to exceptional multiyear droughts, ranking number 1 and number 2 among the driest US states in 2010–2011, respectively (Figure 1). This trend has been recorded by the National Oceanic and Atmospheric Administration [5], while drought conditions can undoubtedly be called cyclical events recurring more or less frequently in sinusoidal cycles.

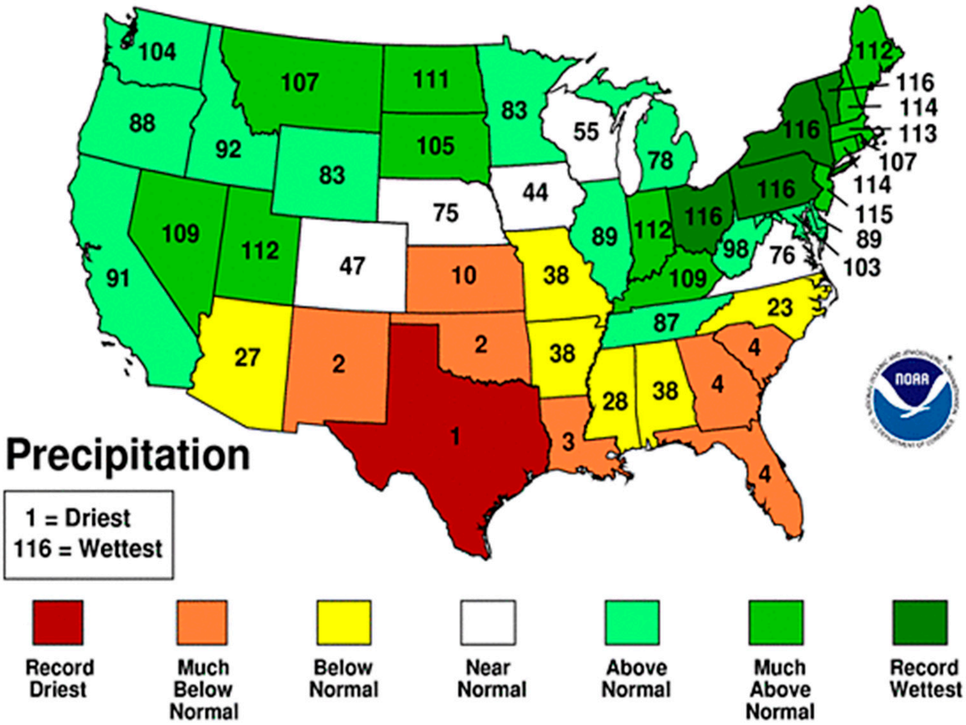

Figure 1. US statewide precipitation ranks (October 2010–September 2011). Source: National Oceanic and Atmospheric Administration [5].

Figure 2 shows a temporal overlap of drought events in both states, which is plausible due to their geographical proximity. In 2011, almost 65% of Oklahoma areas were in exceptional drought, ~95% in extreme drought, and 100% in severe drought. In 2013, even though the area in exceptional drought decreased to 40%, ~98% of the state areas suffered from extreme drought, and 100% from severe drought. Oklahoma also experienced severe and moderate droughts in 2006 and 2009; however, their magnitude was not comparable to the 2011–2014 droughts. A similar situation occurred in Texas, with ~85% of areas in exceptional drought, ~98% in extreme drought, and 100% in severe drought in fall 2011. The 2013 drought in Texas was less severe than in Oklahoma; however, Texas experienced more severe droughts on record in 2006 and 2009.

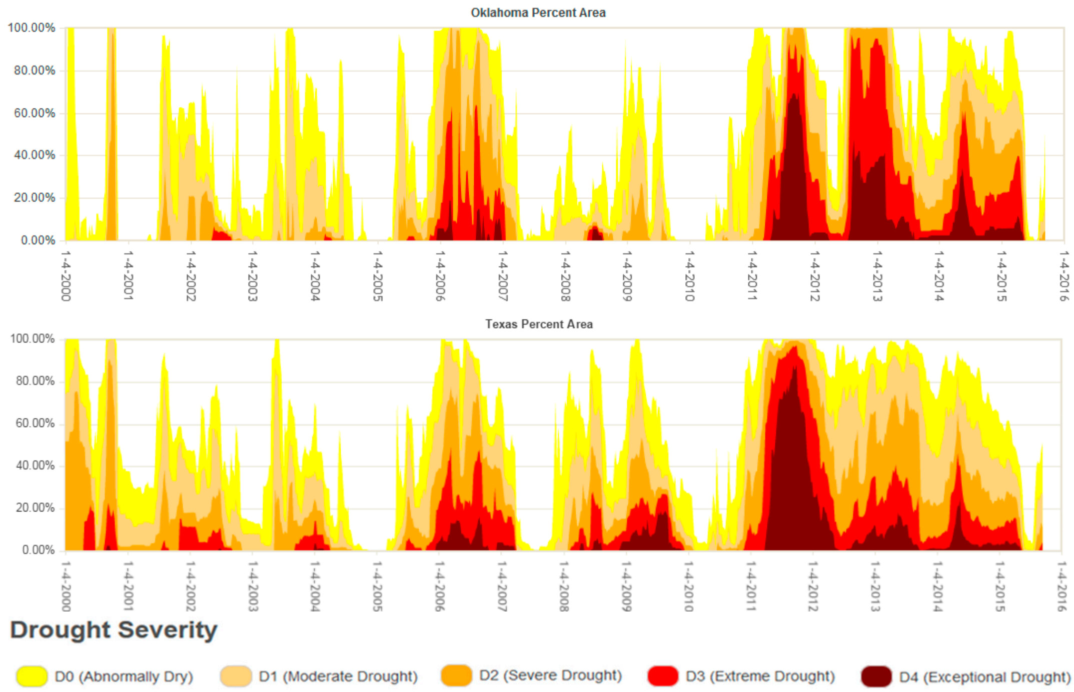

Figure 2. Drought index in Oklahoma and Texas in 2000–2016. Source: Drought Monitor [6], NDMC [7]. Legend: This figure shows categorical US Drought Monitor statistics that describe the percent of the area in a certain drought category, based on precipitation. It excludes areas that are better or worse. The statistics will add up to 100 percent for a given week.

Although droughts have a significant impact on all economic sectors, including municipal water provision, industrial operations, and thermoelectric power generation [8], the agricultural sector is particularly affected. This can be explained with the fact that agriculture is the most intensive user of water for irrigation among all economic sectors both in Oklahoma and Texas. The 2011 drought caused considerable economic losses in agricultural production of nearly $1.6 billion in Oklahoma [9] and $7.6 billion in Texas [10,11], while the entire Texas economy suffered economic losses of around $17 billion [12].

Even though the presented numbers refer to only a one-year drought event, they represent the severity of potential economic impacts as a result of extreme drought conditions, which could potentially recur both in the agricultural sector as well as in other sectors in the future. As the 2011 drought was a record drought, we use this example as a representative data trend for the geospatial analysis of changing groundwater levels in Oklahoma and Texas in 2003–2014 presented in this paper.

The relevance of conservative groundwater use stems not only from the instant meteorological water scarcity, but also from long-term predictions regarding future water availability. According to the Texas Water Development Board (TWDB) [13], Texas' groundwater supplies are expected to fall by 30% in the next 50 years. Similarly, according to the Oklahoma Water Resources Board (OWRB) [14], approximately one-third of the river basins in Oklahoma exhibit poor surface water quality, which may make them unavailable for reliable supply, while bedrock groundwater depletions are anticipated to occur in 34 basins.

In the face of decreasing water availability and an increasing demand for water due to growing population (33% increase in the next 50 years) [14], a question arises about the actual levels of available groundwater resources and possible mitigation/adaptation measures to the current and anticipated droughts in the future. Due to the relevance and urgency of the problem, a multitude of studies emphasized the importance of groundwater evaluation and modelling approaches for sustainable water management [15–21]. Also, some studies applied GIS-based models to address recharge volumes of aquifers from the hydrogeology perspective [22] or groundwater potential zones [23,24]. However, research on geospatial and temporal variability of groundwater resources and a holistic analysis of groundwater changes is still very limited [25,26]. Missing or inconsistent temporal groundwater monitoring records have been a restraining factor for comprehensive research in this field; however, it is common across most US states due to fluctuating human and monetary resources. Figure 3 displays an example in which for the first two wells data on well levels were available only until 2000, while the third well was monitored throughout 2012. In our study we found this common trend both in Oklahoma and Texas.

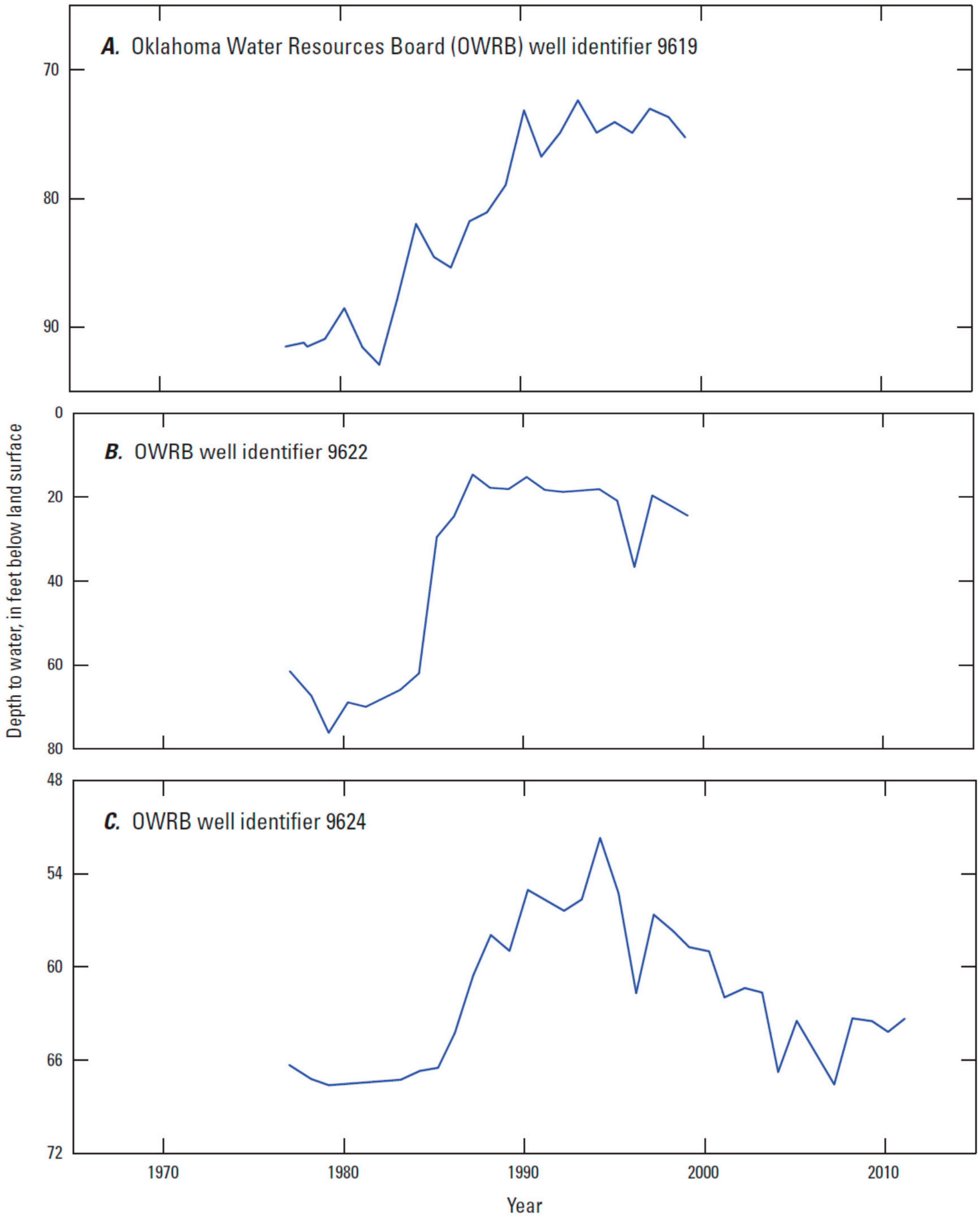

Figure 3. Water levels from Oklahoma Water Resources Board (OWRB) Mass Measurement Program wells. Source: Mashburn et al. [27]. (**A**) Well 9619, (**B**) Well 9622, (**C**) Well 9624.

Furthermore, a multitude of studies analyzed volumetric changes of groundwater resources in different parts of the world to quantify effects of drought. For instance, Konikow [28] evaluated long-term cumulative depletion volumes in 40 separate aquifers in the US by means of calibrated groundwater models, analytical approaches, and volumetric budget analyses. Bhanja et al. [29] analyzed spatio-temporal groundwater storage anomalies in India to prove strong seasonality, with annual maxima observed during the monsoon season and minima during pre-monsoon season. Sakakibara et al. [30] determined comprehensive groundwater recharge processes in a catchment with large seasonal hydrological variations by means of field surveys in the Wangkuai Reservoir watershed in North China, while Zhang et al. [31] estimated groundwater storage indirectly from daily streamflow based on hydraulic groundwater theory. Similarly, Manna et al. [32] used the Chloride Mass Balance method to obtain long-term recharge values in an upland sandstone aquifer of southern California. Studies are also known that investigated impacts of crop rotations on groundwater storage and recharge in agricultural watersheds [33]. Several studies also used GRACE (Gravity Recovery and Climate Experiment) satellite data [34–36] or a combination of satellite data and in-situ observations [37,38], as well as geospatial software tools [39].

The research presented with this paper aims at extending literature in the field by proposing a new model for monitoring groundwater level changes based on a method combination of normalized in-situ averages (rather than absolute water volumes) and the Palmer Drought Severity Index (PDSI) values. As opposed to GRACE measuring groundwater levels based on gravity at a large geographical scale, this model provides a detailed picture of groundwater level changes at each individual well, thus allowing for higher granularity and geospatial resolution of the results.

The proposed geospatial and temporal model for Oklahoma and Texas is used as a case study to explain the benefits of this methodological procedure. The selection of those regions was determined by continued drought events in both states (as described above) and data availability. While Oklahoma has the highest quality weather monitoring network in the world (the Oklahoma Mesonet) [40], Texas has a more comprehensive database with regular groundwater measurements. Those variations in data availability, and statistical calculations conducted for this study, allowed for inference analyses providing a holistic and interactive model of geospatial and temporal groundwater level changes in 2003–2014.

It needs to be emphasized that this paper does not address the groundwater exploitation, total storage, water balances, or policy issues related to aquifer exploitation. Even though those are relevant issues, this research is focused on evaluating spatio-temporal variations in groundwater well levels and developing a tool that can be used for decision-making regarding sustainable water management.

2. Research Objectives

The main goal of this paper is to analyze changes in groundwater well levels in 2003–2014 and determine potential long-term indicators of drought in Oklahoma and Texas. To achieve this goal we developed a geospatial and temporal visualization model with the aim to: (a) identify regional differences in groundwater level changes (geospatial dimension); (b) evaluate changes in groundwater wells over time (2003–2014) (temporal dimension); and (c) emphasize practical benefits of the model by pinpointing potential impacts of those changes in the future as well as potential locations of concern for decision-makers in their efforts to design sustainable water management programs.

As sampling and monitoring of groundwater well levels across US states and regions is often irregular and inconsistent (in some cases it occurs once per year only), the proposed model visualizing normalized changes in groundwater levels over time can also be used for mitigating data paucity. Analyzing past and current groundwater availability is essential for determining water scarcity in the short, mid, and long term. By developing an evaluation tool this research can help decision-makers, water managers, and scientists to recognize geospatial and temporal patterns in groundwater level changes. It can further be used to predict anticipated regional groundwater changes in the future, as well as potential impacts of those changes, thus providing a tool for emergency planning, especially in times of extreme and exceptional droughts.

3. Methods and Data

To evaluate changes in groundwater well levels in different regions of Oklahoma and Texas over time, we developed a four-dimensional (4D) visualization model based on the Ternary Visual Shape Logic introduced for the first time by Ziolkowska and Reyes [41] (Figure 4).

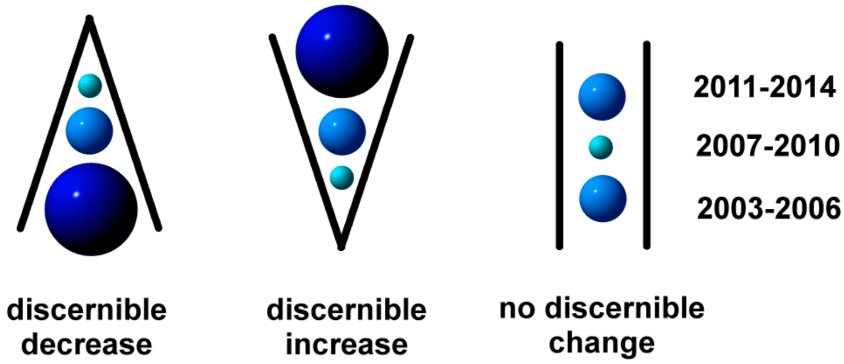

Figure 4. Ternary Visual Shape Logic diagram for the analyzed groundwater changes in 2003–2014. Source: Ziolkowska and Reyes [41].

The model offers a visual representation of temporal changes in groundwater wells. It uses normalized in-situ averages that are further validated with the Palmer Drought Severity Index values. This research does not address absolute water volume changes and balances, as commonly addressed in the literature. Rather, it proposes a more holistic approach of monitoring groundwater level changes even in situations when consistent in-situ measurements are compromised or scattered over time, as is the case with the presented case studies for Oklahoma and Texas. In both states, there is a significant variability in groundwater measurements at the respective wells across the state over the analyzed time span of 12 years. Accordingly, some wells were monitored more frequently (and thus consistent data sets are available for the entire time series), while other wells were monitored less frequently (which resulted in scattered data sets during that time period). For that reason, a comprehensive analysis of water balances is not possible to generate statistically robust results. To mitigate this problem, and provide a comprehensive pattern of groundwater level changes over time, this paper estimates a statistical trend of temporal changes at each well included in the analysis. To validate the correctness of this approach and the robustness of the groundwater model, the trend results have been compared and correlated with the Palmer Drought Severity Index values.

The model was developed for the time span of 12 years (2003–2014), with three-year sections: 2003–2006, 2007–2010, and 2011–2014, which facilitated a temporal analysis of the trends in groundwater levels and drought severity. The time period for this research was selected based on data availability. Data measurements of groundwater well levels before 2002 were very sparse, while the year 2003 was a breakthrough point in terms of the number of monitored wells across Oklahoma and Texas. We attribute this change to technological development and new monitoring instruments that allowed for more frequent and precise groundwater level measurements. Thus, including any analyses before the year 2003 would compromise the robustness of the results, and thus was forgone for the purpose of this study.

The presented model was developed through large data processing, and encompasses four major variables: latitude represented on the *x*-axis, longitude on the *y*-axis, time on the *z*-axis, and the extent of groundwater scarcity (groundwater well levels) as color-shaded spheres. While latitude and longitude allow for displaying geographical dimension, the time variable represents temporal dimension of groundwater level changes.

The model utilizes the US Geological Survey (USGS) water database containing 20,162 wells in Oklahoma and a database from Texas Water Development Board on ~140,000 monitored water wells in Texas. Due to data disparities and missing data points for all wells, we 'cleaned' the data set by determining selection criteria for each well to be included in the model, as follows: (a) wells sampled at least once in each of the three time sections: 2003–2006, 2007–2010, 2011–2014; and (b) wells with at least five samples minimum in the entire time frame. In this way, we specified 7211 water wells in Texas and 390 water wells in Oklahoma. The data was further normalized in order to provide a data-based benchmark and comparison basis for all groundwater data entries. Normalization of the groundwater well levels in both states was conducted for each well separately in two steps. First, minimum and maximum values in the entire raw data set were determined and averaged. In order to provide a more detailed distribution and precise analysis, the sampled values that fell between the minimum and the average value were averaged, thus generating the low-average value. Similarly, the sampled values that were observed between the maximum and the average value were averaged, thus generating the high-average value. This specification provided five hard values (minimum, low-average, average, high-average, and maximum) and categories to constitute a histogram with four bins that were further used to determine distribution of groundwater well levels over time (Figures 5 and 6).

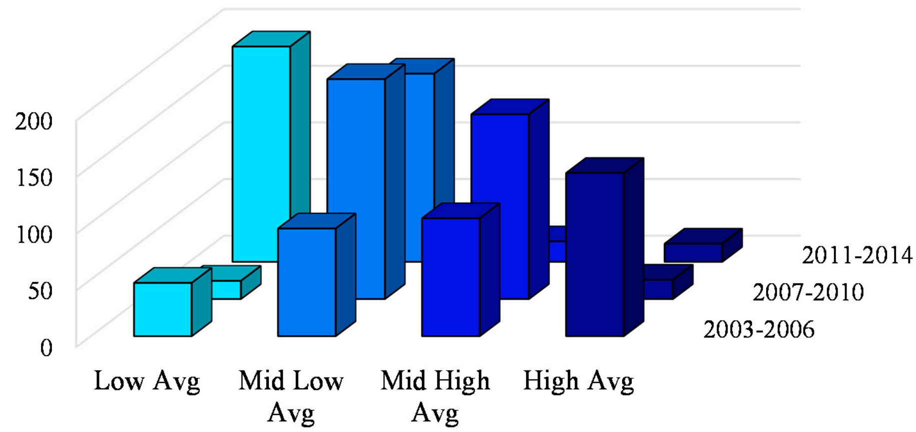

Figure 5. Distribution and categorization of normalized groundwater levels in Oklahoma in 2003–2014. Source: Authors' calculations and visualization.

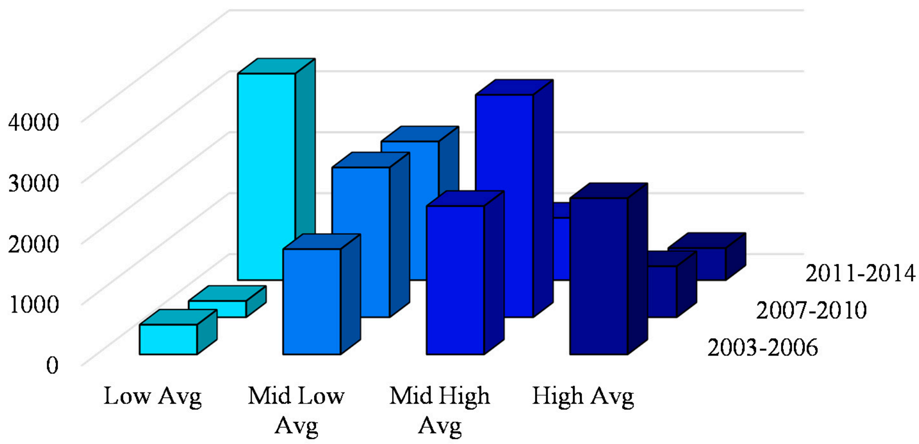

Figure 6. Distribution and categorization of normalized groundwater levels in Texas in 2003–2014. Source: Authors' calculations and visualization.

Second, the raw data set was analyzed for temporal changes by averaging the values for the three time sections: 2003–2006, 2007–2010, and 2011–2014, respectively and assigning them to the corresponding bins. In this way, four values were generated that are represented with four categories of spheres of different colors and different sizes: small cyan spheres (representing the lowest groundwater levels), small medium light blue spheres, big medium blue spheres, and big dark blue spheres (representing the highest groundwater levels). The spheres closest to the ground surface display the years 2003–2006, the spheres second in height from the ground surface display the years 2007–2010, while the spheres highest from the surface represent the most recent years 2011–2014.

In a next step, we used the C++ language to develop computer code and generate KML (Keyhole Markup Language) data files that allow model users to interact with the results both in Google Earth or Cesium and Google Maps (or other platforms) [41]. The model shows three categories of regional trends and variations in groundwater well depletion over the analyzed time span: increasing, decreasing, and inconclusive trends (no change in water levels) in different regions of Oklahoma and Texas. The trends indicate regions of current water scarcity and potential limited water availability in the future.

Due to its interactive feature, the model allows for an analysis of groundwater level changes from a close and a broader perspective in all counties in Oklahoma and Texas over the analyzed time span 2003–2014. The model can be used as a decision-support tool to instantly recognize groundwater scarcity and derive potential socio-economic implications. The strength of the model stems from its ability to visually represent changes in all analyzed groundwater wells in all regions in two states, emphasizing well level gains and losses in different time frames. The large number of raw data is beneficial for a visual representation as discussed with this paper. However, it is overwhelming (due to the large number of data points) for a one-dimensional representation of time series.

To validate the model results and the robustness of our methodological approach, we applied the Palmer Drought Severity Index (PDSI) [42] that has been used extensively in the US and acknowledged as one of the most comprehensive indicators of drought. It incorporates water supply, water demand, temperature, and precipitation. Even though there is a multitude of drought indicators, and PDSI is not the universal measure to evaluate drought [43], we use this indicator due to its reliable and most comprehensive methodology as of today [44]. For validation purposes and geospatial visualization, we represented the Palmer Drought Severity Index as a gradient indicator for the analyzed regions. To prepare the basis for correlation analysis, the PDSI raw data were assigned to the respective drought categories for the three time spans (2003–2006, 2007–2010, and 2011–2014) (Figures 7 and 8) in the same way as for groundwater levels (Figures 5 and 6).

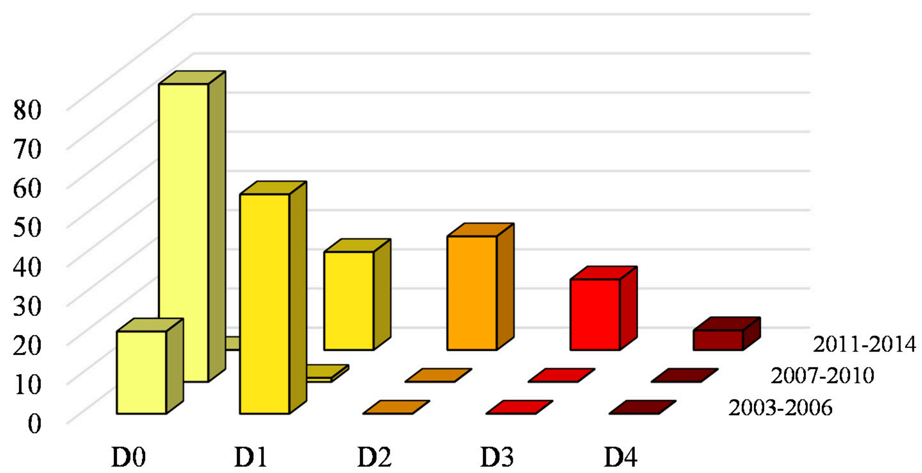

Figure 7. Categorization of averaged drought severity in Oklahoma in 2003–2014. Source: Authors' calculations and visualization.

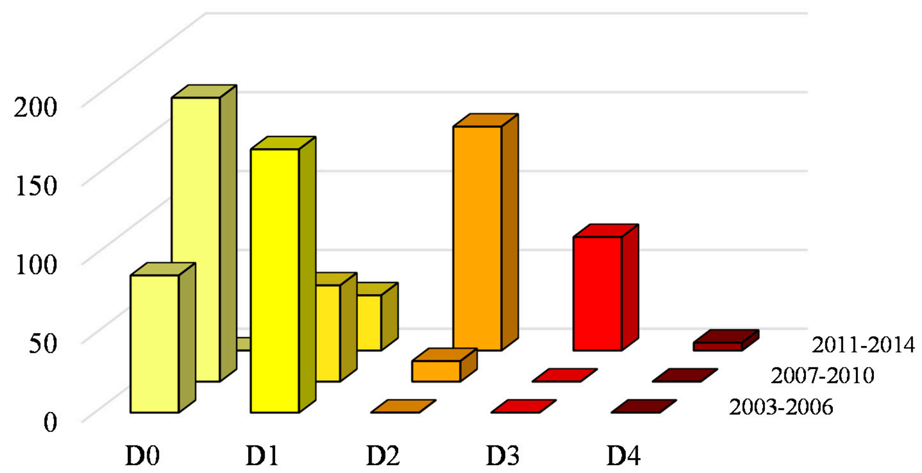

Figure 8. Categorization of averaged drought severity in Texas in 2003–2014. Source: Authors' calculations and visualization.

Data from the Drought Monitor was evaluated for each week in the entire analyzed time period of 2003–2014. A total of 206,544 samples for all counties in Texas and Oklahoma were used for the analysis. The samples represent drought indexes [D0—abnormally dry, D1—moderate drought, D2—severe drought, D3—extreme drought, and D4—exceptional drought] reflecting the percent of the county in each of the drought conditions, respectively (compare with Figure 2). It needs to be mentioned that the presented categorization of groundwater levels (Figures 5 and 6) and drought severity (Figures 7 and 8) has low regional granularity, as it refers to the entire state of Oklahoma and Texas, respectively. The following geospatial distribution offers a more accurate picture of given conditions at a very detailed scale of specific groundwater wells or at the county level. Moreover, a follow-up analysis resonating from this research will allow us to evaluate these correlations for each climate region in both states.

4. Results and Discussion

The model allows for the estimation of the extent of water shortages as a result of droughts in all three analyzed time spans of 2003–2006, 2007–2010, and 2011–2014. It also provides a basis for revealing potential lingering uncertainty resulting from water scarcity and socio-economic implications of groundwater shortages in the future.

The groundwater well levels are represented with the blue-colored spheres (Figure 9) that are clickable and bring up a balloon information window with statistical information (including groundwater levels) in addition to a link to the original well data. Representing all time periods simultaneously is recommended in a model view to interactively navigate/fly through the wells and analyze time series changes over time (Figure 10).

The model shows that groundwater levels in most of the wells have been decreasing since 2003, reaching the peak in the number of wells with the lowest water levels in 2011–2014—the period of exceptional and extreme droughts in Oklahoma and Texas. Only a minority of the wells were inconclusive about the direction of change in groundwater well levels over time. As there is no clear pattern to these inconclusive data points, they can be explained either as outliers or deviating from the trend due to geological formations, rock type, and porosity in the given geographic location. Moreover, there are only a few wells with increasing water levels in both states in that time period. While there is a clear pattern of decreasing groundwater well levels in general, differences also exist from well to well over time. A comprehensive analysis of each well in different time periods can be viewed in the interactive model accessible at: http://www.hitechmex.org/OK_TX/index.html.

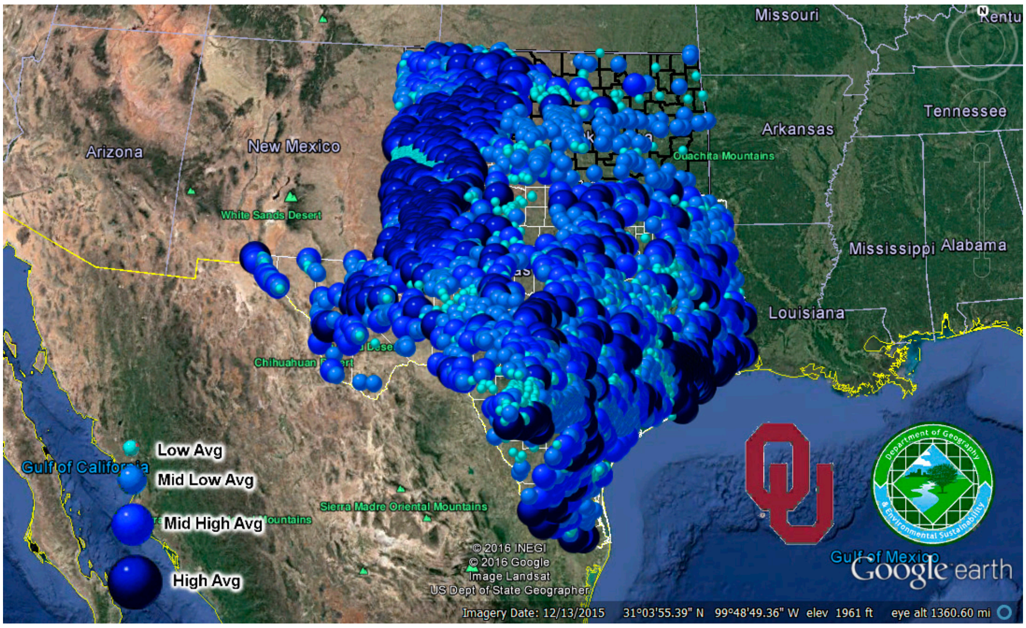

Figure 9. Screenshot of groundwater well levels in 2011–2014 in Oklahoma and Texas. Source: Authors' calculations and visualization.

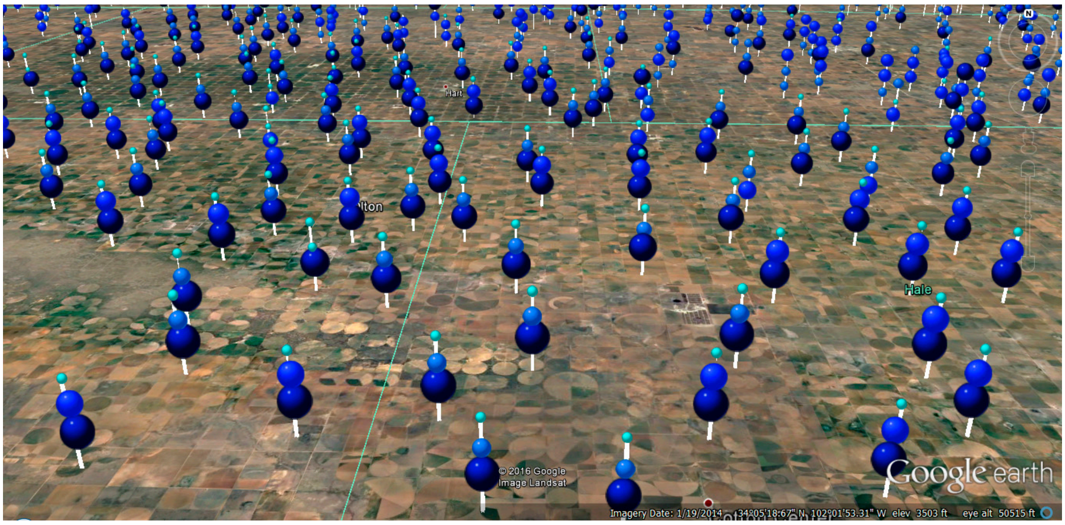

Figure 10. Screenshot of groundwater wells in a Texas region in 2003–2014. Source: Authors' calculations and visualization.

To validate the model results visually, the Palmer Drought Severity Index was applied at this stage as a correlation variable for each county in Oklahoma and Texas. The results of the Palmer Drought Severity Index representation visibly show drought severity in 2011–2014 and weather variations in the three analyzed time spans (compare with Figure 2). By overlapping the PDSI gradient map with the interactive 4D groundwater well model a distinct visual correlation of those two variables unfolds. Figure 11 represents the PDSI gradient in Oklahoma and Texas and also a selection of wells with the lowest water levels in the analyzed time period. It clearly shows that in 2003–2006 the Palmer Drought Severity Index gradient indicated mostly abnormally dry conditions in both states, while the groundwater model shows a low number of wells with the lowest water levels. In 2007–2010, the Palmer Drought Severity Index showed a change in drought severity to moderate drought in some regions, while the number of wells with the lowest water levels either did not change in some regions or increased in regions shadowed with the light orange color (moderate drought according to PDSI). A statistical breakthrough is visualized in the last time period of 2011–2014, with PDSI indicating exceptional and extreme drought in many Oklahoma and Texas regions. At the same time, the number of wells with the lowest water levels spiked markedly. The correlation of the groundwater well model with the independently calculated Palmer Drought Severity Index is a strong indicator of the methodological robustness and validity of our model. While this model is a visual representation of groundwater level changes over the time span of 12 years, it was not the goal of this study to present differences in aquifer storage coefficients across monitored regions or the relationship between water extraction and changes in groundwater levels.

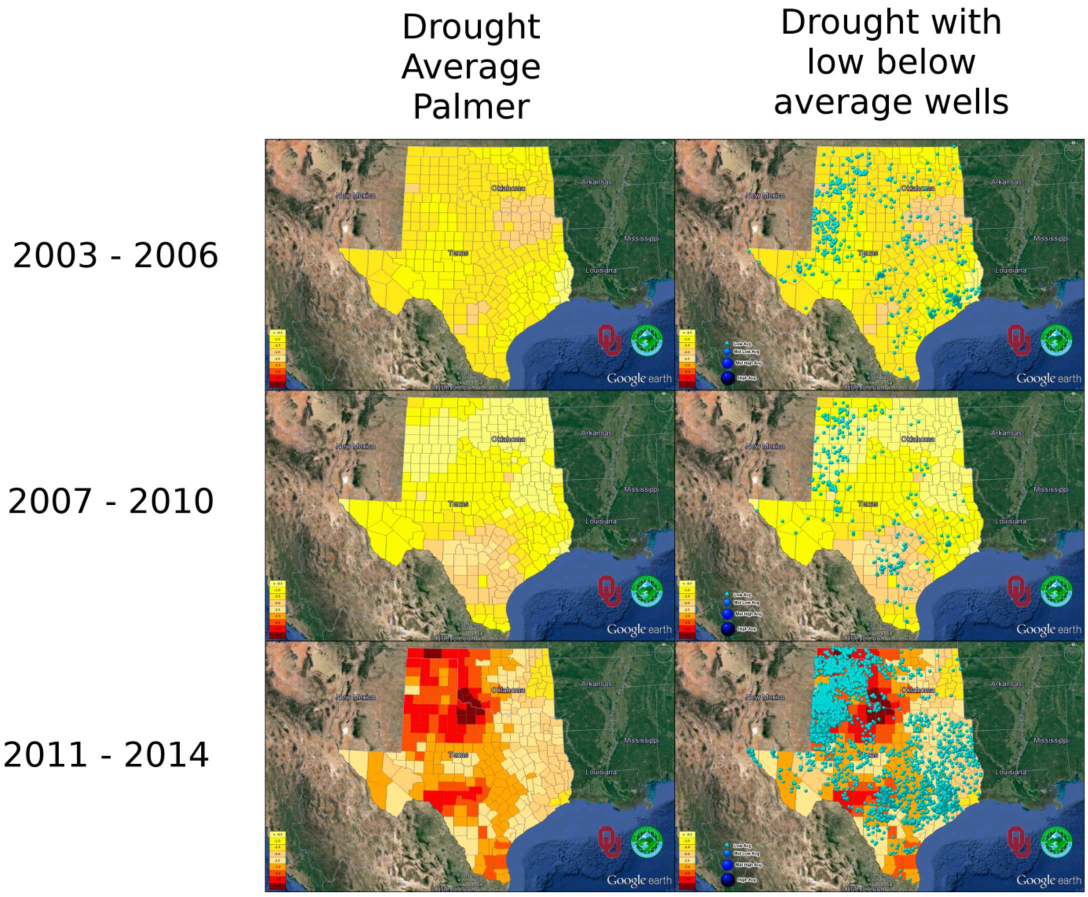

Figure 11. Palmer Drought Severity Index (PDSI) and groundwater wells with the highest water scarcity in 2003–2014. Source: Authors' calculations and visualization.

The visual correlation was further tested statistically according to the formula:

$$r = \frac{1}{n-1} \sum \left(\frac{x - \overline{x}}{S_x} \right) \left(\frac{y - \overline{y}}{S_y} \right) \quad (1)$$

where r—correlation factor; n—number of observations; x—groundwater well levels; y—Palmer drought severity; $\overline{x}$—mean of groundwater level values; $\overline{y}$—mean of drought severity values; S_x—standard deviation of groundwater level values; S_y—standard deviation of drought severity values.

Accordingly, the correlation indicator for Oklahoma amounted to 0.75, while it was 0.95 for Texas, which indicates very strong correlations between the groundwater levels and severity of drought, and thus validates our hypothesis.

The visual model is an interactive tool that can be used for decision-making processes and designing sustainable water management measures. The interactive feature of the model allows the user to learn by navigating though the respective wells, clicking on the respective spheres to retrieve detailed statistical information about temporal variability of groundwater levels at the respective wells and in different regions as a whole, as well as context switching to display temporal correlations between the groundwater level changes and the Palmer Drought Severity Index. However, the model results are only a first step in deriving conclusions on potential mid- and long-term socio-economic impact as a result of drought and decreasing groundwater levels. As accentuated by the model results, the most impacted regions are in the Oklahoma and Texas Panhandle, which are the main agricultural production areas applying water from the Ogallala Aquifer in the southern parts of the High Plains. As discussed at the beginning of this article, the Ogallala Aquifer is non-replenishable, as it contains fossil water. Thus, low groundwater levels displayed by the model are an indicator of severe aquifer depletion (as a combined effect attributed to excessive water withdrawals and insufficient aquifer replenishment), which can lead to unexpected repercussions for the agricultural sector itself, as well as for other economic sectors (municipalities, industry sector, tourist facilities, etc.). Those changes can also further impact the production output, water prices, social welfare, and finally the economic growth in both states. Another question that arises in this context is the extent of drought and its impacts on employment levels and wages in the agricultural sector and beyond. Consequently, the length of drought will determine the scope of the enumerated socio-economic impacts in the mid and long term.

5. Conclusions

The results of this study show a correlation between decreasing groundwater levels and the Palmer Drought Severity Index. Both in Oklahoma and Texas, a significant decrease in groundwater levels has been found in 2001–2014 that correlates with the biggest drought on record. While regional differences have been detected in different regions in both states over time, the general trend of changing groundwater levels corresponds with the recorded regional and state-wide drought severity.

The results were generated and visualized with a geospatial model that allows for an interactive analysis of those trends and patterns in different geographic locations and regions in both states, and over time. In this way, past and current groundwater availability (and water scarcity) at the state, regional, and local level was evaluated holistically with a consistent methodology. The results and the model can be used as a decision-making support tool to assess potential regional groundwater changes in the future, and to analyze potential impacts of those changes. Finally, the outcomes of this research can be useful for long-term planning of emergency situations related to water scarcity.

Furthermore, the results of this study generated a methodological basis for future drought predictions. The positive correlation between the groundwater levels (measured by OWRB, TWDB, and USGS less frequently) and the Palmer Drought Severity Index (measured frequently on a weekly basis) provides a benchmark for determining future groundwater levels (aquifer depletion) even in situations of missing or inconsistent data from in-situ groundwater measurements. Accordingly, in such cases, the Palmer Drought Severity Index could be used as a predictor of groundwater well levels based on statistical inference.

The results and the interactive model can help decision makers with discussions on potential restrictions to water use to be placed on different sectors or users (e.g., farmers, municipalities, industries), as well as with sustainable water allocation. **Model access**: http://www.hitechmex.org/OK_TX/index.html.

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Author Contributions: Jadwiga R. Ziolkowska and Reuben Reyes jointly conceptualized the research idea and methodological framework. Both of them jointly designed the data processing structure and visualization model, and conducted data analysis. Reuben Reyes collected and filtered the data and performed programing. Jadwiga R. Ziolkowska wrote the paper.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Lange, B.; Holman, I.; Bloomfield, J.P. A framework for a joint hydro-meteorological-social analysis of drought. *Sci. Total Environ.* **2017**, *578*, 297–306. [CrossRef] [PubMed]
2. Ge, S.; Gorelick, S.M. Hydrology, Floods and Droughts. Groundwater and Surface Water. In *Reference Module in Earth Systems and Environmental Sciences, from Encyclopedia of Atmospheric Sciences*, 2nd ed.; Elsevier: Amsterdam, The Netherlands, 2015; pp. 209–216.
3. Fendekova, M.; Demeterova, B.; Slivova, V.; Macura, V.; Fendek, M.; Machlica, A.; Gregor, M.; Jalcovikova, M. Surface and groundwater drought evaluation with respect to aquatic habitat quality applied in Torysa river catchment, Slovakia. *Ecohydrol. Hydrobiol.* **2011**, *11*, 49–61. [CrossRef]
4. Steward, D.R.; Allen, A.J. Peak groundwater depletion in the High Plains Aquifer, projections from 1930 to 2110. *Agric. Water Manag.* **2016**, *170*, 36–48. [CrossRef]
5. NOAA (National Oceanic and Atmospheric Administration). National Temperature and Precipitation Maps, 2016. Available online: https://www.ncdc.noaa.gov/monitoring-content/sotc/national/statewidepcpnrank/statewidepcpnrank-201010-201109.gif (accessed on 19 July 2016).
6. Drought Monitor. *US Drought Monitor for Oklahoma*; The National Drought Mitigation Center: Lincoln, NE, USA, 2015.
7. NDMC (National Drought Mitigation Center). *The Drought Monitor—Texas*; University of Nebraska-Lincoln: Lincoln, NE, USA, 2013. Available online: http://droughtmonitor.unl.edu/archive.html (accessed on 10 March 2013).
8. Folger, P.; Cody, B.; Carter, N. *Drought in the United States: Causes and Issues for Congress*; Congressional Research Service Report for Congress 7-5700; CreateSpace Independent Publishing Platformb: North Charleston, SC, USA, 22 April 2013.
9. Stotts, D. *Oklahoma Agricultural Losses from Drought More Than $1.6 Billion*; Oklahoma State University Agricultural Communications Services: Stillwater, OK, USA, 2011.
10. Fannin, B. Updated 2011 Texas Agricultural Drought Losses Total $7.62 Billion. Texas A&M AgriLife Today, 2012. Available online: http://today.agrilife.org/2012/03/21/updated-2011-texas-agricultural-drought-losses-total-7--62-billion/ (accessed on 3 January 2013).
11. Guerrero, B. *The Impact of Agricultural Drought Losses on the Texas Economy*; Briefing Paper; AgriLife Extension, Texas A&M System: College Station, TX, USA, 2011.
12. Ziolkowska, J.R. Socio-Economic Implications of Drought in the Agricultural Sector and the State Economy. *Economies* **2016**, *4*, 19. [CrossRef]
13. Texas Water Development Board (TWDB). *2012 State Water Plan*; Texas Water Development Board: Austin, TX, USA, 2012.
14. Oklahoma Water Resources Board (OWRB). *Oklahoma Comprehensive Water Plan*; Executive Report; Oklahoma Water Resources Board: Oklahoma City, OK, USA, 2012.
15. Sesmero, J.P. Cellulosic biofuels from crop residue and groundwater extraction in the US Plains: The case of Nebraska. *J. Environ. Manag.* **2014**, *144*, 218–225. [CrossRef] [PubMed]
16. Condon, L.E.; Hering, A.S.; Maxwell, R.M. Quantitative assessment of groundwater controls across major US river basins using a multi-model regression algorithm. *Adv. Water Resour.* **2015**, *82*, 106–123. [CrossRef]
17. Foster, T.; Brozović, N.; Butler, A.P. Why well yield matters for managing agricultural drought risk. *Weather Clim. Extrem.* **2015**, *10*, 11–19. [CrossRef]
18. Li, Z.; Quan, J.; Li, X.Y.; Wu, X.C.; Wu, H.W.; Li, Y.T.; Li, G.Y. Establishing a model of conjunctive regulation of surface water and groundwater in the arid regions. *Agric. Water Manag.* **2016**, *174*, 30–38. [CrossRef]

19. Huo, A.D.; Dang, J.; Song, J.X.; Chen, X.H.; Mao, H.R. Simulation modeling for water governance in basins based on surface water and groundwater. *Agric. Water Manag.* **2016**, *174*, 22–29. [CrossRef]
20. Wang, L.; Jackson, C.R.; Pachocka, M.; Kingdon, A. A seamlessly coupled GIS and distributed groundwater flow model. *Environ. Model. Softw.* **2016**, *82*, 1–6. [CrossRef]
21. Decuyper, M.; Chávez, R.O.; Copini, P.; Sass-Klaassen, U. A multi-scale approach to assess the effect of groundwater extraction on Prosopis tamarugo in the Atacama Desert. *J. Arid Environ.* **2016**, *131*, 25–34. [CrossRef]
22. Minor, T.B.; Russell, C.E.; Mizell, S.A. Development of a GIS-based model for extrapolating mesoscale groundwater recharge estimates using integrated geospatial data sets. *Hydrogeol. J.* **2007**, *15*, 183–195. [CrossRef]
23. Singh, P.; Thakur, J.K.; Kumar, S. Delineating groundwater potential zones in a hard-rock terrain using geospatial tool. *Hydrol. Sci. J.* **2013**, *58*, 213–223. [CrossRef]
24. Kuria, N.D.; Gachari, M.K.; Macharia, M.W.; Mungai, E. Mapping groundwater potential in Kitui District, Kenya using geospatial technologies. *Water Resour. Environ. Eng.* **2012**, *4*, 15–22.
25. Lia, B.; Rodell, M. Evaluation of a model-based groundwater drought indicator in the conterminous U.S. *J. Hydrol.* **2015**, *526*, 78–88. [CrossRef]
26. Singh, A. Managing the water resources problems of irrigated agriculture through geospatial techniques: An overview. *Agric. Water Manag.* **2016**, *174*, 2–10. [CrossRef]
27. Mashburn, S.L.; Ryter, D.W.; Neel, C.R.; Smith, S.J.; Magers, J.S. *Hydrogeology and Simulation of Ground-Water Flow in the Central Oklahoma (Garber-Wellington) Aquifer, Oklahoma, 1987 to 2009, and Simulation of Available Water in Storage, 2010–2059*; U.S. Geological Survey Scientific Investigations Report 2013; U.S. Geological Survey: Reston, VA, USA, 2013; Volume 5219, 92p.
28. Konikow, L.F. Groundwater depletion in the United States (1900–2008). USGS Scientific Investigations Report 2013–5079; p. 63. Available online: http://pubs.usgs.gov/sir/2013/5079 (accessed on 14 February 2017).
29. Bhanja, S.N.; Rodell, M.; Li, B.; Saha, D.; Mukherjee, A. Spatio-temporal variability of groundwater storage in India. *J. Hydrol.* **2017**, *544*, 428–437. [CrossRef]
30. Sakakibara, K.; Tsujimura, M.; Song, X.; Zhang, J. Spatiotemporal variation of the surface water effect on the groundwater recharge in a low-precipitation region: Application of the multi-tracer approach to the Taihang Mountains, North China. *J. Hydrol.* **2017**, *545*, 132–144. [CrossRef]
31. Zhang, L.; Brutsaert, W.; Crosbie, R.; Potter, N. Long-term annual groundwater storage trends in Australian catchments. *Adv. Water Resour.* **2014**, *74*, 156–165. [CrossRef]
32. Manna, F.; Cherry, J.A.; McWhorter, D.B.; Parker, B.L. Groundwater recharge assessment in an upland sandstone aquifer of southern California. *J. Hydrol.* **2016**, *541*, 787–799. [CrossRef]
33. Dakhlalla, A.O.; Parajuli, P.B.; Ouyang, Y.; Schmitz, D.W. Evaluating the impacts of crop rotations on groundwater storage and recharge in an agricultural watershed. *Agric. Water Manag.* **2016**, *163*, 332–343. [CrossRef]
34. Xiang, L.; Wang, H.; Steffen, H.; Wu, P.; Jia, L.; Jiang, L.; Shen, Q. Groundwater storage changes in the Tibetan Plateau and adjacent areas revealed from GRACE satellite gravity data. *Earth Planet. Sci. Lett.* **2016**, *449*, 228–239. [CrossRef]
35. Ouyang, W.; Liu, B.; Wu, Y. Satellite-based estimation of watershed groundwater storage dynamics in a freeze–thaw area under intensive agricultural development. *J. Hydrol.* **2016**, *537*, 96–105. [CrossRef]
36. Uddameri, V.; Karim, A.; Hernandez, E.A.; Srivastava, P.K. Sensitivity of Wells in a Large Groundwater Monitoring Network and Its Evaluation Using GRACE Satellite Derived Information. In *Sensitivity Analysis in Earth Observation Modelling*; Elsevier: Amsterdam, The Netherlands, 2017; pp. 235–256.
37. Seyoum, W.M.; Milewski, A.M. Monitoring and comparison of terrestrial water storage changes in the northern high plains using GRACE and in-situ based integrated hydrologic model estimates. *Adv. Water Resour.* **2016**, *94*, 31–44. [CrossRef]
38. Bhanja, S.N.; Mukherjee, A.; Saha, D.; Velicogna, I.; Famiglietti, J.S. Validation of GRACE based groundwater storage anomaly using in-situ groundwater level measurements in India. *J. Hydrol.* **2016**, *543*, 729–738. [CrossRef]
39. Jones, W.R.; Spence, M.J.; Bowman, A.W.; Evers, L.; Molinari, D.A. A software tool for the spatiotemporal analysis and reporting of groundwater monitoring data. *Environ. Model. Softw.* **2014**, *55*, 242–249. [CrossRef]

40. Brock, F.V.; Crawford, K.C.; Elliott, R.L.; Cuperus, G.W.; Stadler, S.J.; Johnson, H.L.; Elits, M.D. The Oklahoma Mesonet: A Technical Overview. *J. Atmos. Ocean. Technol.* **1995**, *12*, 5–19. [CrossRef]
41. Ziolkowska, J.R.; Reyes, R. Geological and Hydrological Visualization Models for Digital Earth Representation. *Comput. Geosci.* **2016**, *94*, 31–39. [CrossRef]
42. Palmer, W.C. *Meteorological Drought*; U.S. Weather Bureau Research Paper; U.S. Government Publishing Office: Washington, DC, USA, 1965; Volume 45, p. 58.
43. Alley, W.M. The Palmer drought severity index: Umitation and Assumptions. *J. Appl. Meteorol. Climatol.* **1984**, *23*, 1100–1109. [CrossRef]
44. Karl, T.R. Sensitivity of the Palmer drought severity index and Palmer's Z-index to their calibration coefficients including potential evapotranspiration. *J. Appl. Meteorol. Climatol.* **1986**, *25*, 77–86. [CrossRef]